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An automatic and non-invasive physical fatigue assessment method for construction workers

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Abstract

The construction industry around the globe is known to have unsatisfactory occupational health and safety records. One of the major reasons attributed to this phenomenon is high physical demands and hostile working environments. Construction workers commonly need to work: (1) for a prolonged period without enough breaks; (2) under harsh climatic conditions; and/or (3) in confined workspaces. These working environments may increase the risk of physical fatigue. To monitor such fatigue, some researchers used on-body sensors (e.g., heart rate monitors and surface electromyography sensors) in construction research. Although these devices allow continuous monitoring of fatigue, they need to be attached to the worker's body, which may interfere work performance. Therefore, computer vision has been developed as an alternative to continuously monitor the posture-based ergonomics of construction workers. However, the causes of physical fatigue involve factors other than poor postures (e.g., external loads, worker' capacity and working procedures). Therefore, a physical fatigue model has been proposed to evaluate physical fatigue through biomechanical analysis, making it possible to assess construction workers' physical fatigue non-invasively and comprehensively. By combining a computer vision-based 3D motion capture algorithm and the physical fatigue assessment model, for the first time, the physical fatigue of construction workers can be estimated automatically and non-intrusively. Two laboratory experiments and one field experiment were conducted to validate the accuracy of the proposed method. Additionally, two case studies were conducted to elucidate the potential of the new method in evaluating the effects of different site layouts and work-rest schedules on workers' physical fatigue levels during different construction tasks.

Keywords: occupational safety and health; construction workers; ergonomic; deep learning; machine learning; computer vision.

1. Introduction

The construction industry around the globe is affected by unsatisfactory occupational health and safety records [1]. One of the major reasons for such health and safety issues is related to high physical demands of construction tasks. Construction workers usually need to work for a prolonged period without sufficient breaks, and/or work in harsh climatic conditions/confined work-spaces. Such working patterns may heighten the risk of developing physical fatigue in construction workers. If workers continue to work under the fatigued condition, they may be at risk of developing work-related musculoskeletal disorders (MSDs), making mistakes, reducing productivity and quality of work, as well as having accidents or fall incidents on construction sites. Therefore, physical fatigue is a severe occupational health and safety problem [2]. According to the Bureau of Labor Statistics [3], 33% of all occupational injuries and illnesses on the US construction sites were related to fatigue and overexertion. Further, hot and humid conditions may accelerate the fatigue development, and increase the risk of heat stroke and death. For instance, heat strokes arising from hot and humid working environments claimed 47 deaths in the Japanese industrial sector in 2010 [4].

The stakeholders in the construction industry, especially those in developed regions, should pay more attention to fatigue detection and prevention because of their ageing workforces and a shortage of manpower. For instance, a study in 2013 found that approximately 44% and 12% of the construction workforce in Hong Kong aged over 50 years and 60 years, respectively [5]. Another study has projected that there will be a shortfall of 10,000 to 15,000 construction workers from 2017 to 2021 in Hong Kong [6], which accounts for approximately 5.4% to 8.1% of the total workforce in 2017 [7]. Given the fact that older workers are more prone to physical fatigue due to declined physical work capacity and muscle strength, it is paramount to optimize the sustainability of the current construction workforce by improving their occupational health and safety. Since physical fatigue poses a major challenge to occupational health and safety, fatigue monitoring and management is utmost important.

While self-reported questionnaires are traditionally used to evaluate construction workers' fatigue [8,9], this data collection method is not pragmatic for continuous fatigue monitoring. Therefore, some researchers have tried to use on-body sensors to objectively monitor fatigue [4,10–13]. Although prior studies have proven the concept, attaching multiple sensors to construction workers' bodies inevitably interfere their work performance. Further, these sensors may be uncomfortable to wear and may cause skin irritation. To overcome these limitations, the current research developed a new approach by adopting a computer vision technology and biomechanical analysis to monitor construction workers' physical fatigue. Specifically, a computer vision-based 3D motion capture algorithm was developed to model the motion of various body parts as captured by an RGB camera during the performance of construction tasks. Inverse dynamics was used to estimate the joint-level torque based on the assumptions of a fatigue model. From the empirical findings, the fatigue assessment model was applied to enable individualized fatigue monitoring.

For the first time, this technology was validated for automatic assessments of construction workers' physical fatigue in a laboratory experiment (*Section 5.2*) and a field experiment (*Section 5.3*). This technology has the potential to reduce the overexertion and fatigue of construction workers, and to improve the occupational health and safety of the construction industry. The development of such a system will also enable non-invasive fatigue monitoring of workers in various industries other than construction.

2. Literature review

Fatigue is defined as tiredness and reduced functional capacity that occurs during and at the end of the workday [14]. Fatigue includes physical fatigue, mental fatigue, and emotional fatigue. The current study focused on physical fatigue. Numerous methods have been proposed to measure physical fatigue level, including subjective and objective methods. The subjective method relies on workers' self-perceived physical fatigue. *Borg rate of perceived exertion (RPE) scale* and *Borg CR10 scale* are two commonly used scales asking workers regarding their perception of fatigue on a scale from 6 to

20 or from 0.0 to 12.0 [15], where higher scores indicate more fatigue. The self-report method is easy to implement but not suitable for investigating construction workers' physical fatigue because: (1) the reporting process may interrupt the normal work activity; (2) the self-report method only provides the final fatigue status rather than monitoring the fatigue development process; and (3) the reported data may be inaccurate/inconsistent given the subjective nature of perceived fatigue. Given the above, it is important to develop an objective, non-intrusive, continuous and accurate physical fatigue monitoring method. The following section reviews previously reported objective physical fatigue assessment methods.

2.1 Physiological indicators

Physical fatigue involves a physiological process, which can be monitored by physiological indicators such as cardiovascular indicators and electronic indicators. Cardiovascular indicators include heart rate, skin temperature and breathing rate, which usually increase as a consequence of high physical strains [13,16,17]. These indicators can be measured by wearable sensors tied/attached to workers' body. However, these sensors may hinder workers' performance during work routine. In addition, these sensors need to be charged every "several hours" within a day, making it difficult to monitor physical fatigue for a prolonged period.

A widely-used electronic indicator for physical fatigue detection is surface electromyography (sEMG) [18]. sEMG is a non-invasive technique to measures the myoelectric activity during muscle contraction and relaxation cycles [19]. The myoelectric signals are captured by electrodes, then amplified, filtered and transferred to digital signals. When a muscle develops fatigue, the median frequency of the digital signal will decrease [20]. Previous studies have used sEMG to measure construction worker's muscle fatigue in laboratories [10,21]. Although sEMG can accurately measure muscle fatigue, the method may not be applicable on the construction sites. Since a pair of sEMG electrodes should be attached to the skin of each target muscle group, it is infeasible to attach a lot of electrodes to workers for whole-body muscle/physical fatigue measurements. Further, as sweating and body movement can cause significant artifacts to sEMG signals, it is impossible to monitor muscle fatigue in real time on construction sites.

In summary, while physiological indicators can objectively assess physical fatigue, workers need to wear some sensors in order to detect physiological changes, which may hinder work performance, cause discomfort, and may have questionable accuracy for continuous physical fatigue assessments on construction workers.

2.2 Ergonomics indicators

Ergonomics indicators estimate physical fatigue based on workers' postural data and external load data. Such data is mainly affected by the working process (e.g., site layout and work-rest schedule), which in turn is related to construction site management. Numerous studies have adopted posture-based methods and computation models to assess/estimate workers' physical fatigue. This section provides an overview of various posture analysis methods and modes of data collection.

2.2.1 Ergonomic indicator-based methods (Table 1)

Posture-based method. The working posture is a critical biomechanical factor leading to physical fatigue. Previous research evaluated work postures to estimate the risk of physical fatigue development in construction workers [2]. The posture data was usually collected by observation, 2D cameras, or wearable motion sensors. Some studies assessed physical fatigue based on joint angles. By observing the joint angles of various body parts in a given work posture (e.g. trunk flexion/extension angles, shoulder flexion/abduction angles, and elbow/knee flexion angles), each joint angle was classified into a particular range of motion category, which is given a specific physical fatigue score [22–24]. Another method is to first identify the working posture (e.g. standing up, back bending, squatting, etc.) through observation and then estimate the corresponding physical fatigue based on the posture [25]. Although awkward postures may increase the risk of physical fatigue, other factors (e.g., lifting construction materials, or using heavy tools) may also modify the risk of developing physical fatigue. Therefore, using the posture-based method alone without considering other factors may underestimate the presence of physical fatigue.

Posture and exerted force-based methods. Some ergonomic scales assess physical fatigue by considering both postures and exerted forces, including Key Item Method (KIM) [26], NIOSH lifting equation [27], Ovako Working Posture Analysis System (OWAS) [28], Occupational Repetitive Actions (OCRA) [29], Rapid Upper Limb Assessment (RULA) [30], and Rapid Entire Body Assessment (REBA) [31]. Like the posture-based method, the working posture is rated on these scales based on observation. When assessing exerted forces, the external forces/loadings are classified into different categories according to the absolute value, such as 0~5kg, 5~10kg and over 10kg. The overall physical fatigue score is calculated by summing the posture-based score and the exerted force-based score. Some scales also consider the work pattern. For example, RULA and REBA take the work repetitiveness and duration into account. The final physical fatigue score will be higher if a task is repeated more than four times per minute or lasts for more than a minute.

While these scales are easy to use and can provide quantitative workload assessments, they may not be suitable for evaluating risk of overall physical fatigue in construction workers because some of these scales only assess a particular body part (e.g. OCRA evaluates the upper body only). Further, these scales were originally developed to evaluate the works of manufacturing workers, whose works mainly involve repetitive motions with external loads in a static posture. However, the works of construction workers are more diverse and less repetitive, making it difficult to assess physical fatigue based on repetitiveness or duration alone. Importantly, since using different scales to assess the same workload may yield different results [26], it is difficult to compare findings across studies. To overcome these limitations, the current study developed a physical fatigue assessment method that suits the complex nature of construction activities by using biomechanical calculations.

Biomechanical calculation-based methods. From the exerted forces and postures, biomechanical analysis can estimate joint workloads based on joint forces or torques. Several joint workload estimation tools have been developed based on biomechanical calculations, including 3DSSPP, OpenSim, and AnyBody Modelling System [32–34]. Specifically, 3DSSPP estimates the joint loading under a static condition, while OpenSim and AnyBody focus on muscle workload. Both 3DSSPP and OpenSim have been applied in previous construction industry research to assess workers' ergonomic risks, and physical fatigue [35,36]. However, these methods usually require the use of a complex motion capture system. For example, a typical whole-body motion sensor set for OpenSim requires the acquisition of 50 markers' data on the participant's body using multiple cameras [37]. It is impractical for workers' fatigue monitoring on construction sites.

2.2.2 Modes of data collection (Table 1)

All the aforementioned physical fatigue assessments require the acquisition of kinematic data (i.e., postures or joint angles) by various data collection methods.

Observation. As mentioned above, this method has been used to collect kinematic data in previous research [38,39]. However, observation may not be applicable in the construction field. Since the observation results depend largely on the observer's experience and subjective judgement, they may not be accurate enough for physical fatigue analysis. Further, as this method is time-consuming and labor-intensive, it is infeasible to monitor physical fatigue of multiple workers on a construction site [40].

Inertial measurement units (IMUs). An IMU is an electronic device that measures three-axis angular speed and three-axis orientation automatically and accurately. They have been used to collect construction workers' kinematic data for ergonomic analysis [2]. Based on the joint angle data and the posture-based method, the physical fatigue level can be assessed automatically [13,24,25]. The main disadvantage, however, is the requirement of attaching IMU sensors to the human body, which may interfere workers' work. In addition, such sensors may not be suitable for prolonged usage because they may lead to discomfort [40,41].

Motion capture systems. Motion capture systems (e.g., the VICON system and Optotrak) are commonly used in laboratories for 3D motion capture and analysis. To capture motion data, an examiner needs to set up multiple cameras in a laboratory and then put reflective markers on the designated locations of an individual's body. The system estimates the 3D position and movement trajectory of each marker based on the signals of the reflective markers captured by the cameras. The reported accuracy of the VICON system is as high as 2 millimeter [42]. The results are usually further processed by biomechanical calculation software, such as OpenSim, to conduct muscle loading/biomechanical analysis [33]. However, since these motion capture systems require the installation of at least 4 cameras within 10 m from the attached reflective markers on the target worker's body in order to capture the whole-body posture, it is impractical to use on construction sites [43].

Vision-based motion capture methods. These are a non-intrusive solution for the motion capture of working postures. Depth cameras, such as Kinect, have been proven to be an effective tool to collect construction workers motion data in various indoor environments [36,44,45]. Depth cameras could generate range images, of which each pixel includes both RGB value and the distance to the camera. The 3D human skeleton, i.e. the 3D locations of the key joints, could be estimated based on the range images. The accuracy of depth cameras, however, might be very low in outdoor environments because the distance is usually calculated based on the infra-red signals, which are easily interfered under direct sunlight [45]. To solve this problem, researchers have tried to extract working postures from RGB images captured by ordinary cameras with the help of deep learning algorithms. Construction workers' 2D postures have been successfully extracted from RGB images [23,46–48]. From the outputs of 2D posture recognition methods, postures are automatically classified into different categories (e.g., squatting, bending or lifting) based on the relative joint angle ranges. However, this method can only be used for posture-based ergonomic analyses rather than physical fatigue assessments because it cannot precisely measure joint angles, which prevent the estimation of joint kinematics and loading.

To conduct detailed physical fatigue assessments on construction sites, it is important to develop an accurate and non-intrusive 3D motion capture method that suits the outdoor environment. The aforementioned data collection methods are not suitable for construction sites because: (1) manual observation is subjective and inaccurate; (2) IMUs and motion capture systems are expensive and may lead to uncomfortableness; (3) depth camera cannot work in outdoor environments; and (4) 2D posture recognition methods from RGB images cannot support physical fatigue analysis based on 3D postures.

A recent advance in computer vision, the single-len 3D posture estimation algorithm, provides a potential solution to solve previous limitations [49]. The algorithm can model a 3D human skeleton from 2D RGB video frames. When applied on construction sites , this method can collect construction workers' 3D joint locations from construction site videos. Compared with previous 3D posture data collection methods, the method can work in outdoor environments without the need of any wearable sensors. As such, the single-len 3D posture estimation algorithm was applied in this study to collect construction workers 3D postures accurately and non-invasively in outdoor environments.

2.3 Muscle fatigue development models (Table 1)

Several muscle fatigue models have been developed to predict physical/muscle fatigue according to various fatigue development mechanisms [50].

Calcium ions cross-bridge mechanism model. The amount of calcium ions is important for the muscle fiber contraction. High concentrations of calcium ions can activate ATP (Adenosine Triphosphate) enzymes, which catalyze the hydrolysis of ATP to release energy for muscle fiber contraction [51]. Accordingly, a mathematical model, named calcium ions cross-bridge mechanism model, was proposed to simulate the negative relation between calcium ions and muscle fatigue. The model has been validated in a prior experiment [52]. Although the model can predict muscle fatigue correctly, it is not suitable for industrial application due to its complexity. For example, nearly 20 variables are required for the estimation of quadriceps fatigue [50]. In addition, some variables (such as normalized amount of calcium-ion-troponin complex, the duration of each muscle activation, and the number of activations) are difficult to measure during the construction work routine.

Force-PH relationship model. The accumulation of lactic acid in a muscle is the major cause of muscle fatigue. The close relation between low pH and decreased muscle forces has been observed due to the increased intracellular concentrations of lactate and hydrogen ion [51]. According to the muscle-force relation, a mathematical model was developed to predict muscle fatigue through curve fitting of the temporal pH level in the process of muscle activation and recovery [53]. Although the muscle activation and recovery curve fitted well with the pH level, no prior experiment has validated the model. Further, it is infeasible to measure the construction workers' intracellular pH on construction sites continuously and non-intrusively.

Joint torque model. This new model was proposed to predict physical fatigue based on joint torque [54]. The model was first theoretically built based on the muscle motor unit theory [55]. The theory assumes that a muscle consists of many motor units with different force generation capabilities and recovery properties [55]. Some motor units generate large forces and develop fatigue quickly, but they also recover quickly after fatigue. Conversely, some motor units generate smaller amount of forces for a longer duration, but they recover slowly after contraction. As a result, when a muscle contracts, the muscle capacity should first decrease rapidly then slowly; and during the recovery process, the muscle capacity should also increase first rapidly then slowly. Muscle fatigue decreases the capacity of corresponding body segments to cope with the external load, which can be expressed as the physical fatigue level of a joint in the model. The model simulates the suggested joint fatigue and recovery process through the modelling of joint torques, maximum voluntary contraction and fatigue/recovery rate. The model has been validated in a series of human studies on the elbow joint fatigue during some static tasks [54,56]. The model has also been applied in virtual construction environments to assess fatigue level of shoulder joints of construction workers [57]. Given the simplicity and applicability of the model, it has the potential to be applied on construction sites to assess workers' physical fatigue level although previous studies only validated the model in laboratory or virtual environments.

2.4 Summary

While various posture analysis methods and muscle fatigue models have been developed, not all of them can be applied to monitor physical fatigue in construction workers in the field. Table 1 shows the comparisons of different physical assessment methods and modes of data collection based on assessment indicators, accuracy, focused body parts, working pattern (if the method requires repetitive working pattern), working environments (lab environments/indoor environments/outdoor environments), and intrusiveness. The following research gaps are identified from the comparisons:

1) Some data collection methods affect accuracy of kinematic data. For example, the self-report methods are not accurate/reliable due to the subjectivity of the reported data. The accuracy of the observed posture data is examiner-dependent. In addition, although some methods estimate 2D posture data from RGB images, the 2D images can only be used to determine the working postures (e.g. squatting or standing) rather than accurate joint positions or angles.
2) Since the works of construction workers are diverse, different body segments are susceptible to fatigue differently. Therefore, a good fatigue assessment should estimate the physical fatigue level of the whole body. Although some methods can accurately assess physical fatigue, they only focus on certain body parts. For example, a pair of sEMG electrodes can only measure fatigue of a single muscle, while the calcium-ion cross-bridge model only estimates quadriceps fatigue.
3) As the working procedures of many construction tasks do not involve monotonic repetitive movements, a pragmatic fatigue assessment method should not be restricted to a fixed working pattern. However, some existing posture-based ergonomic evaluation methods determine physical fatigue risk scores according to the duration or frequency of a particular working posture [58] , which is not suitable for construction tasks.

4) Many construction workers work outdoor, thus a good physical fatigue assessment method for construction workers should work well in outdoor environments. Some data collection methods, such as sEMG sensors and depth cameras, can only work in laboratory or indoor environments.
5) Some sensor-based methods are invasive. For example, the sEMG electrodes need to be directly attached to the workers' skin; the IMU sensors need to be tied tightly to the workers' limbs. Such sensors may result in discomfort and compromised work performance.

In short, a practical fatigue assessment method for construction workers should be accurate and non-invasive and focuses on whole-body fatigue without being limited to a given environment or working pattern.

Table 1 The comparison of physical fatigue assessment methods and modes of data collection

	Assessment method		Assessment indicators	Data collection methods	Accuracy	Body parts	Working pattern	Environment	Invasiveness
Subjective	Self-report		Self-perception of physical fatigue	Questionnaire Interview	Low (subjective data)	**Whole-body**	**No restriction**	**Outdoor**	Intermittent recording procedures
Objective	Physiological indicators	Cardiovascular indicators	Heart rate, skin temperature or breathing rate	Wearable sensors	**High**	**Whole-body**	**No restriction**	**Outdoor**	Discomfort due to the sensor attachment
		Myoelectric indicator	The median frequency of sEMG signals	sEMG electrodes	**High**	Low back	**No restriction**	Lab	Discomfort due to the attachments of electrodes
	Ergonomic indicators	Pose or/and exerted forces- based assessments	Ergonomic risks due to awkward postures, large exerted forces, and prolonged or repetitive task patterns	Observations by an examiner	Low (observer dependence)	**Whole-body**	Repetitive and regular	**Outdoor**	**Non-invasive**
				IMU sensor	**High**	**Whole-body**	**No restriction**	**Outdoor**	Discomfort due to the attachments of sensors
				Depth Camera	**High**	**Whole-body**	**No restriction**	Indoor	**Non-invasive**
				RGB camera + 2D posture data	Low (Only posture classification)	**Whole-body**	**No restriction**	**Outdoor**	**Non-invasive**
		Biomechanical analysis	Joint-level physical fatigue	Motion capture system	**High**	**Whole-body or body segments**	**No restriction**	Lab	More than ten markers and four cameras
	Muscle fatigue models	Calcium ions cross-bridge model	Muscle-level physical fatigue	-	**High**	Quadriceps	**No restriction**	Lab	-
		Muscle force-pH model	Maximum muscle capacity	-	**High**	-	**No restriction**	Lab	-
		Joint-torque model	Muscle- or joint- level physical fatigue	RGB camera + 3D posture data	**High**	**Whole-body or body segments**	**No restriction**	**Outdoor**	**Non-invasive**

IMU represents inertial measurement unit; sEMG represents surface electromyograph.

3. Research objectives and contributions

Given the abovementioned research gaps, the aim of this study was to develop an accurate and non-invasive physical fatigue assessment method that could be suitable for construction field environments using the 3D motion data collection method and joint-torque fatigue model. In particular, accurate 3D motion data is collected from RGB video frames, which continuously collect workers' 3D motion data without the need of attaching any sensors to the workers on construction sites. The resulting data can be entered the joint-torque fatigue analysis model without any restrictions on working patterns. Additionally, the model can estimate workers' fatigue at the whole-body-level and the joint-level. The main contributions of this research were to: (1) apply a deep-learning-based method to automatically and continuously collect construction workers' 3D motion data from video frames; (2) automatically evaluate construction workers' physical fatigue on construction sites. Such a method has the potential to assist the academia and the industry to understand and prevent physical fatigue of construction workers by continuous and automatic fatigue assessments.

4. Methodology

To develop a new quantitative physical fatigue evaluation method for construction workers, it involved three steps (Figure 1). The first step was to collect 3D motion data automatically and non-invasively using an ordinary 2D RGB camera. The second step involved the measurements of the exerted force and human body parameters, which enabled the estimation of joint torques. The third step involved the estimation of a physical fatigue index based on a muscle fatigue development model.

Figure 1 An overview of the physical fatigue assessment method

4.1 3D motion captured from 2D video

To ensure the non-intrusive collection of 3D motion data for biomechanical analyses, the 3D motion data of the target worker must be collected accurately and automatically without interfering work activities. Therefore, a single RGB camera-based 3D motion capture algorithm was developed to solve this problem [49]. Figure 2 layouts the framework of the algorithm.

Figure 2 The single RGB camera-based 3D motion capture algorithm

The algorithm first identifies key joints (neck, shoulders, elbows, wrists, hips, knees and ankles) and the locations of the joint-related pixels in the 2D RGB images using Stacked Hourglass Networks [59]. The network is composed of multiple hourglass modules placed end to end. Each hourglass model is a convolutional neural network, which extracts features from an RGB image through convolution operations. An hourglass module first reduces the original RGB image to different resolutions, and then extracts and combines features across multiple resolutions so that the hourglass module considers both local and global features, corresponding to the joint information and the whole-body information of the target individual. From the 2D locations of each joint, another network is then trained to infer the 3D locations of each joint [49]. The basic assumption of the network is that the ratio of two bones of the same person should be a constant. The network was trained on MPII datasets, which contain the 2D and 3D pose data of postures such as squatting, standing and walking [60]. Then the network was trained to minimize the differences in bone length ratios between the inferred 3D postures and the ground truth 3D postures in the MPII dataset.

4.2 Inverse dynamics for joint-level torque analysis

The biomechanics of human musculoskeletal system are complex because the mechanical properties of bones, joints, tendons, and muscles of individuals are affected by various factors (e.g., age, gender, weight and height). Additionally, the stress-strain relations of bones, joints, tendons, and muscles also vary with the exerted forces. To facilitate the internal load analysis, this research made the following assumptions in the calculation: (1) the human body was simplified as a lever system connected with hinge joints; (2) each lever was rigid with a constant length regardless of the external load; and (3) workers' motions on construction sites were slow and steady, which meant the lever system was in an equilibrium status. Based on the above assumptions, the force balance equation and torque balance equation were used to solve the joint torques. Figure 3 presents the simplified human skeleton model for the biomechanical analysis, which contains 15 key joints including the torso and four limbs. The coordinates are a right-hand-rule system. The positive direction of the y-axis is upward. Figure 4 shows the force and torque of a given segment.

Figure 3 The simplified biomechanical human skeleton model

Figure 4 Forces and moments of a given segment

4.2.1 Computing joint reaction forces

Newton's equation was used to calculate joint reaction forces. For a given segment, the equation can be expressed as Eq.1.

$$\boldsymbol{F}_{Pr} + \boldsymbol{F}_{Ch} + \boldsymbol{G} = \boldsymbol{0} \qquad \text{Eq.1}$$

Where,

$\boldsymbol{F}_{Pr} = (F_{Pr,x}, F_{Pr,y}, F_{Pr,z}) \in \mathbb{R}^3$ is the joint reaction force at the parent joint [N];

$\boldsymbol{F}_{Ch} = (F_{Ch,x}, F_{Ch,y}, F_{Ch,z}) \in \mathbb{R}^3$ is the joint reaction force at the child joint [N];

$\boldsymbol{G} = (0, -mg, 0) \in \mathbb{R}^3$ is the gravity of the segment [N]; m is the mass of the segment [kg]; g=9.8 m/s^2;

The positive direction indicates the upward direction, which is the same as the positive direction of the y-axis in Figure 3.

In this research, the mass of each segment (m) was calculated based on the segment percentage of total body weight, which could be referred to [61] for details. Briefly, according to the skeletal model in Figures 3, there is no child joint reaction force in the force equilibrium equations of lower arms and shanks. The forces are replaced with ground reaction force and hand load forces due to the tools or materials holding in hands. In this research, the hand load force was assumed to be the weight of the tools/materials, and the ground reactions force was assumed to be the sum of hand load force and the participant's body weight. Given the ground reaction forces, the joint reaction forces of knees could first be calculated, while the joint reaction forces of other joints were estimated hieratically.

4.2.2 Computing joint torques

The torque balance equation was used to calculate joint torques. Figure 4 shows the torques on a given segment, where A is the parent joint, B is the child joint, and C is the gravity center point. The sum of all the torques acting on the parent joint is equal to zero. The torques include parent joint torque, child joint torque, and the torques generated from the segment's self-weight and the joint reaction force on the child joint. The torque generated from the parent joint reaction force is zero. Eq. 2 is the torque balance equation.

$$\begin{gathered}\mathbf{T_{pr}} + \boldsymbol{T_G} + \boldsymbol{T_{F_{Ch}}} + \boldsymbol{T_{Ch}} = \mathbf{0} \\ \mathbf{T_G} = \overrightarrow{\mathbf{AC}} \times \mathbf{G} = \mathrm{r}\overrightarrow{\mathbf{AB}} \times \mathbf{G} \\ \boldsymbol{T_{F_{Ch}}} = \overrightarrow{\mathbf{AB}} \times \mathbf{F_{Ch}}\end{gathered} \qquad \text{Eq.2}$$

where $\boldsymbol{T_{Pr}}$ is the reaction torque at the parent joint A; $\boldsymbol{T_G}$ is the torque produced by $\boldsymbol{G}$; $\boldsymbol{T_{F_{Ch}}}$ is the torque produced by $\boldsymbol{F_{Ch}}$; $\boldsymbol{T_{Ch}}$ is the reaction force at the child joint B. The unit of torque is [N·m]. The positive direction is clockwise.

$\overrightarrow{\mathbf{AC}}$ is the vector from the parent joint to the center of mass of the segment; $\overrightarrow{\mathbf{AB}}$ is the vector from the parent joint to the child joint; *r* is the ratio of $\overrightarrow{\mathbf{AC}}$ to $\overrightarrow{\mathbf{AB}}$, which represents the location of the center of mass. The value of *r* is given in [61].

4.3 Joint physical fatigue assessment

This module aimed to determine joint physical fatigue according to the current loads on joints and the associated load history of these joints. The fatigue and recovery model developed by Ma et al. [54] was applied to predict construction workers instantaneous and cumulative fatigue alongside the posture and pressure data.

The instantaneous joint physical fatigue index $IF(t)$ is defined as the decrease of joint capacity in this paper (Eq.3). Γ_{max} represents the maximum joint capacity, which means the maximum torque that the joint can hold. $\Gamma_{cem}(t)$ represents the current joint capacity. At the start of a task, the joint capacity $\Gamma_{cem}(t)$ equals to Γ_{max}, so $IF(t) = 0$. In work status, the joint capacity $\Gamma_{cem}(t)$ will decrease, so $IF(t)$ will increase. In rest status, the joint capacity $\Gamma_{cem}(t)$ will increase, so $IF(t)$ will increase. Figure 5 represents the above process.

$$IF(t) = \frac{\Gamma_{max} - \Gamma_{cem}(t)}{\Gamma_{max}} \times 100 \qquad Eq.3$$

Figure 5 An example of the instantaneous joint physical fatigue index in work and rest status

The maximum joint capacity Γ_{max} is estimated based on the correlation between ages, gender, weights, height and ethnicities from Shaunak, Ang et al. (1987) and Meldrum, Cahalane et al. (2007) [62,63].

The current joint capacity $\Gamma_{cem}(t)$ at work state was simulated based on the muscle motor unit theory [55]. According to the theory, muscles generate torques because of the activation of motor units. Some units have a high muscle force generation capacity, but the capacity decreases rapidly (easy to fatigue). Other units have a lower muscle force generation capacity, which decreases slowly (fatigue resistant). When a given muscle is activated to work against a large external force, both type of motor units will be activated but the latter one would last longer. Based on the above theory, the joint capacity decreases more rapidly under a higher workload because motor units responsible for generating large force would show fatigue easier. Further, under the same constant workload, the rate of joint capacity reduction will decelerate [55]. Eq.4 depicts the above process, where *k* is a constant value, and equals to 1 min^{-1}. $\Gamma(t)$ means the joint torque at time *t*, which is the calculation results of 4.2.2. $\Gamma_{cem}(t)$ can be calculated as the integral of $d\Gamma_{cem}(t)/dt$ (Eq.5).

$$\frac{d\Gamma_{cem}(t)}{dt} = -k\frac{\Gamma_{cem}(t)}{\Gamma_{max}}\Gamma(t) \qquad Eq.4$$

$$\Gamma_{cem}(t) = \Gamma_{cem}(t_0)\, exp(-\frac{k}{\Gamma_{max}}\int_{t_0}^{t}\Gamma(u)du) \qquad Eq.5$$

The current joint capacity $\Gamma_{cem}(t)$ *at rest state.* When the muscles of a certain body part are in a resting state, the respective joint capacity will recover. As shown in Figure 5, the joint muscle capacity increases when a worker is taking a rest. According to the muscle motor unit theory, the recovery process is represented by $(\Gamma_{max} - \Gamma_{cem}(t))$ in Eq.6, where R is set as 2.4 min^{-1}, indicating the average rate of recovery according to Liu, Brown et al. (2002)[65]. $\Gamma_{cem}(t)$ can be calculated as the integral of $\mathrm{d}\Gamma_{cem}(t)/dt$ (Eq.7).

$$\frac{d\Gamma_{cem}(t)}{dt} = R(\Gamma_{max} - \Gamma_{cem}(t)) \qquad \textit{Eq.6}$$

$$\Gamma_{cem}(t) = \Gamma_{cem}(t_0) + (\Gamma_{max} - \Gamma_{cem}(t_0))(1 - e^{-Rt}) \qquad \textit{Eq.7}$$

The cumulative joint physical fatigue index $CF(t)$ development speed is positively correlated with the external load and negatively related to muscle strength capacity [64]. The formula of the joint physical fatigue model is expressed in Eq.8, where *t* represents time. $CF(t)$ represents cumulative joint physical fatigue level. In Eq.8, $\Gamma_{max}/\Gamma_{cem}(t)$ is the reciprocal of current relative joint capacity, representing the personal factors. $\Gamma(t)/\Gamma_{cem}(t)$ is the current relative joint load, representing the external factors.

$$\frac{dCF(t)}{dt} = \frac{\Gamma_{max}}{\Gamma_{cem}(t)} \frac{\Gamma(t)}{\Gamma_{cem}(t)} \qquad \textit{Eq.8}$$

Finally, given $\Gamma_{cem}(t)$, the cumulative joint physical fatigue index $CF(t)$ can be calculated as the integration of $dCF(t)/dt$. Figure 6 is an example of the cumulative joint physical fatigue index $CF(t)$, which increases rapidly in work state due to the decrease in muscle capacity and increases slowly or even decreases in rest state due to the increase of the muscle capacity.

Figure 6 An example of the cumulative joint physical fatigue index at the work and rest states

In addition, in this study, the instantaneous/cumulative whole-body physical fatigue indices are defined as the average of the instantaneous/cumulative joint physical fatigue indices of all joints of an individual.

5. Experiments and results

To validate the accuracy and usability of the proposed method, three experiments were conducted to validate the proposed approach during some construction tasks: 1) a laboratory experiment to validate the accuracy of the motion capture method; 2) a laboratory experiment to validate the accuracy of the physical fatigue assessment method; and 3) a field experiment to validate the usefulness of the new approach in estimating physical fatigue.

5.1 Testing the accuracy of the 3D motion estimation method

5.1.1 Experiment design

This experiment aimed to validate the accuracy of the 3D motion estimation method by comparing the estimated 3D joint locations from video image frames and the ground truth 3D joint locations measured with an IMU system (3-Space™ Wireless 2.4GHz DSSS, OH, USA).

Participants: A healthy male graduate student, aged 27 years, was recruited to perform three simulated construction tasks in a laboratory, including material handling, plastering, and rebar tying. He could terminate the task if he experienced discomfort.

Equipment: The participant was required to wear the IMU system to determine the ground truth for the 3D motion data. The IMU sensor has an accuracy of 1° [66]. Thirteen IMU sensors were tightly tied to the head, chest, back, waist, upper arms, forearms, thighs and shanks to determine the joint positions (Figure 7). At the same time, an RGB video camera captured the participant's postures during the task. The sampling frequency of the IMU and video camera were 50 Hz and 30 fps, respectively.

Simulated construction tasks: After putting on the IMU sensors, the participant was instructed to perform a simulated material handling task, a plastering task, and a rebar tying task. The material handling task involved picking up 4 bricks from the floor with both hands and then carry the bricks to to a target place on the floor 3 meters away. The participant needed to repeat the task for 10 times. For the plastering task, the participant mimiced the motion of plastering an area of 5 meters width and 2 meters height. For the simulated rebar tying task, the participant tied a mesh of plastic bars at every intersection. The mesh of the plastic bars consisted of 5 x 5 bars placed perpendicular to one aonther to form a mesh. The distance between the bars in both direction was 30 centimeters.

To calibrate the IMU system before each task, the paricipant was requried to stand with both feet closed together and both arms stretched out to the sides and held parallel to the ground to form a T shape. The IMU data was synchronized with the RGB images during the task performance.

5.1.2 Experiment results

The data from the IMU and the synchronized images were compared to assess the accuracy of the RGB image-based 3D motion recognition results. Table 2 shows the error of the 3D motion capture method of the key joints, including head, left shoulder (LS), right shoulder (RS), left elbow (LE), right elbow (RE), left wrist (LW), right wrist (RW), left hip (LH), right hip (RH), left knee (LK), right knee (RK), left ankle (LA) and right ankle (RA). The error was measured as the distance between the estimated joint locations and the ground truth joint locations [49,67]. The mean error of the 3D location of each joint was 3.90cm with a standard deviation of 1.59cm.

Figure 7 The inertial measurement unit sensors and the tasks of the laboratory experiment

Table 2 The error of the 3D motion capture method *unit: cm*

Task		**Head**	**LS**	**RS**	**LE**	**RE**	**LW**	**RW**	**LH**	**RH**	**LK**	**RK**	**LA**	**RA**	**Mean**
Rebar tying	Mean (SD)*	6.12 (1.99)	4.17 (1.22)	3.11 (1.19)	4.76 (1.15)	4.38 (1.11)	5.40 (1.24)	5.79 (1.10	0.88 (0.32)	0.88 (0.32)	0.88 (0.32	1.86 (0.89)	3.62 (2.21)	4.10 (2.45)	3.53 (1.40)
Bricklaying	Mean (SD)	7.94 (1.94)	5.69 (1.36)	5.58 (1.25)	4.23 (0.88)	3.71 (0.86)	6.38 (1.02)	5.57 (1.27)	1.13 (0.35)	1.13 (0.35)	1.13 (0.35)	3.02 (1.20)	9.10 (1.62)	9.47 (1.66)	4.93 (0.93)
Plastering	Mean (SD)	10.38 (1.45)	8.85 (1.01)	8.77 (1.31)	7.58 (0.93)	8.98 (1.95)	10.31 (1.07)	12.97 (2.00)	0.58 (0.17)	0.58 (0.17)	0.58 (0.17)	2.11 (1.00)	2.74 (1.22)	3.14 (1.24)	3.24 (1.32)

Mean (SD)	8.14 (2.26)	6.24 (1.70)	5.82 (1.93)	5.52 (1.30)	5.69 (1.70)	7.36 (1.71)	8.11 (2.27)	0.87 (0.34)	0.87 (0.34)	0.87 (0.34)	2.33 (1.03)	5.16 (2.84)	5.57 (2.96)	3.90 (1.59)

*SD represents standard deviations
** LS represents left shoulder; RS represents right shoulder; LE represents left elbow, RE represents right elbow; LW represents left wrist; RW represents right wrist; LH represents left hand; RH represents right hand; LK represents left knee; RK represents right knee; LA represents left ankle; RA represents right ankle.

5.2 Testing the accuracy of the physical fatigue assessment method

This experiment aimed to validate the accuracy of the physical fatigue assessment method by comparing the average joint capacity with the participant's heart rate, which is a classical and widely-used assessment indicator for physical fatigue assessment [15].

5.2.1 Experiment design

Participants: We recruited four health male participants, aged between 20 and 30 years to perform a simulated material handing task in a laboratory. They were allowed to terminate the task had they experienced intolerable fatigue, chest pain, shortness of breath, or muscle cramp. The demographic parameters (age, gender, height, and weight) of the participants were documented before the experiment.

Equipment: The participants wore a heart rate monitor at the chest (Equivital^{TM} LifeMonitor, UK) to monitor the heart rate. The task would be terminated had a participant's heart rate exceeded the corresponding maximum heart rate (90%* [(220 – age) - resting heart rate] + resting heart rate) for more than 2 minutes. The heart rate data was recorded every five seconds automatically by the heart rate monitor. At the same time, an RGB camera (1,920×1,080 pixels per frame, 50 frames per second) captured the participant's postures during the task.

Simulated material handling task: To ensure the accuracy of the heart rate monitoring, the experiment was conducted in a controlled laboratory environment (25°C). After putting on the heart rate monitor, participants were required to perform a simulated material handling task with both arms. Notably, the participant was instructed to lift a box (6 kg, 37 cm * 33 cm * 26 cm) from a 3 m x 4 m working platform (1 m height) and carried the box with bilateral elbows at 90° flexion to randomly walk around the platform with for about 5 minutes. The participant was given a five-second break every minute.

Data process: The normalized heart rate was standardized to the respective the heart rate at baseline (set as 100). The video data and the demographic data were used to calculate the current joint capacity and the maximum joint capacity of eight key joints (both shoulders, elbows, hips and knees). First, the eight joint capacity results were converted from 50 fps to 0.2 fps by averaging the results over every 250 frames. From the current joint capacity and the maximum joint capacity, the instantaneous joint physical fatigue indices were calculated according to *Eq.3*. Finally, the instantaneous whole-body physical fatigue index was calculated as the average of the eight instantaneous joint physical fatigue indices. Pearson's correlation test was conducted to quantify the correlation between the average instantaneous whole-body physical fatigue index and normalized heart rate.

5.2.2 Experiment results

Four participants (mean age of 28.3 years, mean height of 1.73m, and mean weight of 60.33kg) were recruited (Table 3) participated in the study.

Table 3 The demographic parameters of the four male participants and the corresponding video records

Participant	Height [m]	Weight [kg]	Age [years]	Task duration [second]	Total number of frames
#1	1.78	69.3	30	326	16,300
#2	1.70	61	24	260	13,000
#3	1.73	60	29	298	14,900
#4	1.69	51	30	309	15,450

Figure 8 shows the comparison between the calculated instantaneous whole-body physical fatigue index and the measured heart rate. The instantaneous whole-body physical fatigue index (solid line) increased in work state and decreased in rest state. Similarly, the normalized heart rate (dotted line) increased during work and decreased at rest. Figure 8 shows that the two lines have similar trends. Pearson's correlation coefficients showed significant positive correlations between the instantaneous whole-body physical fatigue index and the normalized heart rate ($p < 0.01$, Table 4).

Figure 8 The comparisons of the average instantaneous physical fatigue index and the normalized heart rate of the four participants

Table 4 The results of Pearson's correlations between average instantaneous physical fatigue indices and normalized heart rates of different individuals

Participant	Correlation coefficient	*p*-value
#1	0.74	2.33×10^{-8}
#2	0.74	6.28×10^{-7}
#3	0.78	1.63×10^{-7}
#4	0.68	2.37×10^{-4}

5.3 Testing the usefulness of the physical fatigue assessment method

This experiment aimed to validate the usefulness of the physical fatigue assessment method through a scaffolding task and a masonry task. One participant was recruited to perform the scaffolding task and another participant was recruited to perform the masonry task.

5.3.1 Experiment design

For the scaffolding task, the participant was instructed to construct a cube with two-meter-long steel tubes and couplers, as shown in Figure 9. The construction site layout is shown in Figure 10. The working area was the location where the cube was built. The storage area was the place where the steel tubes and couplers were stored. The straight-line distance from the storage area to the work area was about 6 m. During the experiment, the participant first carried a tube weighted approximately 12 kg from the storage area to the working area, then assembled the tubes with couplers. This process was repeated for 16 times to finish the task. The 16 times were chosen because our pilot study showed that this number of repetitions caused fatigue in the participant. Two RGB cameras (smartphone cameras) were fixed on tripods to record the participants' motion. The height of the tripods was 1.2 m. The tripods were 3 meters away from the working area (Figure 10).

Figure 9 The process of the scaffolding task and the finished cube

Figure 10 The site layout of the scaffolding task

For the masonry task, the participant was asked to build a concrete block wall as shown in Figure 11. Each concrete block weighted approximately 16kg. Concrete blocks were placed 1 m away from the target concrete block wall location. The thickness of the wall was 190 mm and the height was 1,520 mm. The wall comprised eight layers. The width of each layer was either 780 mm or 970 mm (Figure 11). To build the wall, the participant first bent knees to pick up a block, then turned around to lay the block. The motion was repeated until a layer of the brick wall had been properly placed. Then the participant checked the layer with a level and evened it out with a thicker layer of mortar. The procedure was repeated until the target wall was built. Two RGB cameras (smartphone cameras) were fixed on tripods to record the participants' motion. The height of the tripods was 1.2 m. One of the tripods was 3 meter away from the working area, while the other one was 1 meter away from the working area (Figure 12).

Figure 11 The process of the masonry task and the finished concrete block wall

Figure 12 The site layout of the masonry task

5.3.2 Experiment data

The demographic data (Table 5) and the video records of the two tasks (Table 6) were entered to the fatigue model.

Table 5 The demographic parameters of the participants

Participant	**Height [m]**	**Weight [kg]**	**Age**	**Gender**
The scaffolder	1.70	75	27	Male
The masonry	1.75	71	40	Male

Table 6 The information of the video records of the two experiment tasks

Task	**Duration [second]**	**Frame size**	**Data rate**	**Frame rate [fps]**	**No. of frames**
Scaffolding	1,433	640×480	45,00kbps	30	42,990
Masonry	378				11,330

Data processing. The anthropological parameters of the participants were used to estimate the respective body segment mass, the location of the center of mass of each body segment, and maximum joint capacity as explained in Section 4.3. To eliminate the effects of visual obstruction, two cameras recorded the participants' motions simultaneously. The videos from two cameras were compared frame by frame and the one with fewer obstructions was selected to eliminate the effects of obstructions by the scaffold or the concrete brick wall.

5.3.3 Experiment results

Figure 13a-13d show the instantaneous and cumulative joint physical fatigue indices of eight joints (bilateral shoulders/elbows/hips/knees) during the scaffolding task and the masonry task. The instantaneous joint physical fatigue index reflects the specific fatigue level of each frame (Eq.3), while the cumulative joint physical fatigue index reflects the accumulated fatigue level from the start to a certain frame (Eq.8).

Figure 13a The instantaneous joint physical fatigue index of the key joints during the scaffolding task

Figure 13b The cumulative joint physical fatigue index of the key joints during the scaffolding task

Figure 13c The instantaneous joint physical fatigue index of the key joints during the masonry task

Figure 13d The cumulative joint physical fatigue index of the key joints during the masonry task

In Figure 13a and Figure 13c, there was a general increase in the instantanuous joint phyiscal fatigue indices over time during both tasks. It is noteworthy that there were significant fluctuations in the instantaneous joint physical fatigue curves of hips and knees during the scaffolding task (Figure 13a). The fluctuations might be attributed to the fact that the participant needed to return to the storage area without carrying any weights after fixing a steel tube. The participant's body segments were in a relaxed state without staying in an awkward posture or carrying an external load. Thereby, the instantaneous joint physical fatigue indices of the eight joints recovered during that period.

Figure 13b and 13d show the cumulative fatigue levels of the eight key joints (bilateral shoulders/elbows/hips/knees) during the two tasks. All cumulative joint physical fatigue level curves during the two tasks show a continuous increasing trend. When the instantaneous joint physical fatigue indices increased, the cumulative joint physical fatigue indices increased sharply. Conversely, when the instantaneous joint physical fatigue indices decreased, the joint cumulative physical fatigue indices increased slowly or even decreased.

As is shown in Figure 13a-13d, the proposed physical fatigue assessment method could estimate joint-level physical fatigue development over time. Figures 13b and 13d demonstrate that the participant's lower limbs (including both hips and knees joints) had higher cumulative fatigue levels than upper body joints. Specifically, the left hip and the right knee demonstrated the highest and the second highest cumulative fatigue levels. This phenomenon suggested that these two joints were easier to fatigue. In the masonry case (Figure 13c and 13d), the participant's left knee and left hip had the highest and the second highest fatigue levels. The final cumulative joint physical fatigue index of the left leg was about five times higher than the right leg. This indicated that the participant might involve more asymmetrical weightbearing during masonry task.

6. Case studies: assessing construction worker's physical fatigue under different working conditions

6.1 Case #1: The influence of construction site layout on physical fatigue level

Different construction site layout may result in different working postures and working durations, which may affect fatigue and productivity. Taking the scaffolding task as an example. If the distance between the working area and the storage area increases, workers need to carry the tubes for a longer period. However, workers also benefit from a longer resting period when they return to the storage area without carrying an external load. As such, the proposed physical fatigue assessment method can help provide objective comparisons between various construction site layouts to improve productivity and prevent physical fatigue.

Given the above, the objective of this case study was to compare the effects of different distances between the work area and the storage area on physical fatigue level of an individual during a scaffolding task. In particular, the distances between the working area and the storage area was set at 3m, 6m and 12m (similar to the scaffolding task in Experiment 5.3).

Figure 14a and 14b illustrate the instantaneous and cumulative whole-body physical fatigue indices for completing the scaffolding task among three different site layout plans. Figure 14a and 14b show that longer the distance between the work area and the storage area, lower the fatigue level. Figure 14c shows the final cumulative whole-body physical fatigue indices for completing the task under different conditions. The final cumulative fatigue levels in Figure 14c are equivalent to the whole-body cumulative physical fatigue indices at the end of the scaffolding task in Figure 14b. Figure 14d demonstrates the durations for completing the task under the three conditions. Figure 14c and 14d highlight that longer the distances, lower the final whole-body cumulative physical fatigue index but longer task completion time. In other words, there was a trade-off between alleviating the risk of physical fatigue and reducing productivity.

Figure 14a The comparison of the instantaneous whole-body physical fatigue indices during the scaffolding task with different distances between the working area and storage area (3m/6m/12m)

Figure 14b The comparison of the cumulative whole-body physical fatigue indices during the scaffolding task with different distances between the working area and storage area (3m/6m/12m)

Figure 14c The comparison of the final cumulative whole-body physical fatigue indices after the scaffolding task with different distances between the working area and storage area (3m/6m/12m)

Figure 14d The comparison of the duration of the scaffolding task with different distances between the working area and storage area (3m/6m/12m)

6.2 Case #2: The influence of work-rest schedule on fatigue level

While it is well known that taking proper breaks are an effective way to mitigate physical fatigue, construction workers usually do not have enough time to rest at work. This experiment aimed to evaluate the influences of rest on fatigue mitigation by quantitative fatigue assessments.

In Experiment 5.3, the worker performed the masonry task continuously without any breaks. In this case study, the worker had a rest after finishing each layer of the wall. The rest time was set at 5 and 10 seconds. The fatigue assessment results were shown in Figure 15. Compared with continuous working, taking short breaks slowed down the extent of instantaneous whole-body physical fatigue during the masonry task. Continuous working without a break led to approximately 75% decreases in worker's average maximum joint capacity at the end of the task. However, 5- and 10-second breaks could keep the worker's average joint capacity at 60% and 75% of the maximum capacity upon completion of the task.

Figure 15 The comparison of the instantaneous whole-body physical fatigue indices during the masonry task with different rest time (0/5/10 seconds)

7. Discussion

This study, for the first time, used deep learning-based 3D posture estimation algorithms, biomechanical analysis, and a physical fatigue mathematical model to non-intrusively and automatically assess physical fatigue of construction site workers. The laboratory experiments confirmed the accuracy of the methodology, while the field experiments and case studies demonstrated the feasibility of the approach in assessing the construction worker's physical fatigue in various outdoor environments. The two case studies also demonstrated the effects of workplace layout and breaks on the physical fatigue of construction workers.

Compared to previous fatigue assessment methods for construction workers, the proposed approach has several advantages. First, the data collection is continuous and non-invasive. Second, the results are objective, and quantifiable. Third, the fatigue analysis has no limitations on working patterns (regular or repetitive working postures). Fourth, the method considers multiple factors including workers' capacity, postures and joint loading history. These advantages make this approach suitable for estimating physical fatigue of construction workers during complex and dynamic construction works.

Despite numerous advantages, the current study had a few limitations. First, while accurate 3D motion capture and analysis were needed for the ensuing fatigue assessments, the 3D motion capture method adopted in this research might be affected when there were severe visual obstructions or when the cameras were installed in high places. Accordingly, future studies should train a 3D motion estimation model with more on-site pictures, especially those with obstructions and/or top-down angles.

Second, the current method needs to measure the mass of materials or tools in order to estimate the joint loading, which may limit its applicability in real construction projects. Future studies should focus on the incorporation of automatic mass measuring methods. For instance, the camera can first identify the material or the tool and then estimating the mass with reference to material databases.

8. Conclusions

A non-invasive and automatic approach was proposed to assess construction workers' physical fatigue using computer vision and a biomechanics computation model. Specifically, a 3D motion estimation method was used to detect workers' 3D motion data by a monocular RGB camera, while the anthropological and kinematics data were used to estimate the torques of multiple upper limb, lower limb and trunk joints. The resulting data was entered a fatigue computational model to calculate the real-time joint capacity and fatigue index based on the history of joint capacity. In laboratory experiments, the high correlation between the estimated physical fatigue index and heart rate data proved the accuracy of the approach. Field experiments explored the application of the approach in construction sites management. The results showed that the method could provide suggestions on working postures thorough analyzing joint fatigue level and assess construction workers' physical fatigue under different site-layout and work-rest schedule.

This research, however, didn't consider the influence of visual obstructions on the accuracy of 3d posture data and automatic external load estimation. Future studies could focus on construction workers' joint location inference under visual obstructions and automatically estimating the weights of tools or materials.

If applied on construction site, the novel fatigue assessment method enables construction site workers to understand the fatigue level of various body segments during various construction tasks. The fatigue assessment results can also help construction site managers evaluate the construction workers' fatigue risks, set site-layout and work-rest schedules to different construction tasks, and enhance the safety and health performance of the construction industry.

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