Automation in Construction 82 (2017) 154–165

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Monitoring fatigue in construction workers using physiological measurements

Ashrant Aryal, Ali Ghahramani, Burcin Becerik-Gerber *

Sonny Astani Dept. of Civil and Environmental Engineering, Viterbi School of Engineering, Univ. of Southern California, KAP 217, 3620 South Vermont Ave., Los Angeles, CA 90089-2531, USA

ARTICLE INFO

Article history:
Received 30 July 2016
Received in revised form 24 January 2017
Accepted 14 March 2017
Available online 23 March 2017

Keywords:
Fatigue assessment
Thermoregulation
Wearable sensing
Construction safety
Physiological monitoring

ABSTRACT

Fatigue is one of the factors leading to reduction in productivity, poor quality of work and increased risk of accidents in construction. Existing established methods of assessing fatigue include surveys and questionnaires, which are cumbersome to implement at construction sites. This study presents a novel approach for real time monitoring of physical fatigue in construction workers using wearable sensors. Changes in the heart rate, thermoregulation and electrical brain activity during a simulated construction task were monitored from 12 participants using a heart rate monitor, infrared temperature sensors and an EEG sensor. Borg's RPE was used as a subjective scale to collect the level of fatigue experienced by the participants. Boosted tree classifiers were trained using the features extracted from the heart rate and temperature sensor signals and used to predict the level of physical fatigue. Only physical fatigue was assessed as none of the participants developed any sign of mental fatigue during the study. The results show that physical fatigue can be monitored using wearable sensors. The classification accuracy, based solely on features extracted from average of skin temperature data, was 9% higher than based solely on heart rate data, and combining the information from both sensors resulted in the best accuracy of 82%. The results also show that monitoring thermoregulation from temple can be more useful compared to other studied monitoring sites, the classification accuracy based only on data from the temple was 79%. This accuracy is significantly higher compared to the classification accuracy based only on heart rate data (59%).

1. Introduction

The construction industry, one of the largest industries in the world, is also associated with high number of accidents. Based on a report released in 2005, the International Labor Organization (ILO) estimated there are at least 60,000 construction related fatalities around the world each year [1,2]. In the industrialized countries, the ILO estimates 35% to 40% of the fatalities to occur in the construction industry, which employs less than 10% of the total workforce [1]. Despite the construction industry's small share of the total workforce (4.8% [3]) in the United States, it had the highest number of fatalities, 984 fatalities (20.3%) in 2015 [4]. The same year, the incidence rate of nonfatal injuries in the construction industry, caused by overexertion was 10.6 per ten thousand workers, requiring a median of 13 days away from work [5]. Although safety performance in the U.S. construction industry improved significantly between 1973 and 2004 due to adoption of highly effective injury prevention strategies, there has not been any significant improvement in the injury statistics in the past decade, indicating that the industry has reached saturation with respect to the traditional injury prevention strategies and new safety innovations are needed [6,7].

Construction work typically involves physically demanding tasks often performed in harsh environmental conditions, which can cause fatigue and lead to poor judgment, poor quality of work, increased risk of accidents and reduction in productivity [8,9]. Fatigue has been associated with experiencing difficulties with physical and cognitive functions [10] and identified as a potential risk factor for slip-induced falls (40% of fatalities in 2014) [11], one of the “fatal four” causes of fatalities in the construction industry according to the Occupational Safety and Health Association (OSHA) [12]. 20% to 40% of different craft workers on a construction site routinely exceed generally accepted physiological thresholds for manual work [8]. Physical fatigue and impaired mental capacity pose a greater risk towards accidents in hot and cold environmental temperatures [13]. Although it is difficult to quantify the direct impacts of fatigue on construction safety due to lack of robust methods for real time fatigue monitoring, resulting in lack of fatigue related studies in occupational safety studies [14], it is one of the factors that has a negative impact on workers' safety and performance [15].

The objective of this study is to investigate if thermoregulatory changes (i.e., changes in the blood flow due to vasocontraction and vasodilation) could be used for assessing fatigue buildup, compared to the

* Corresponding author.
E-mail address: becerik@usc.edu (B. Becerik-Gerber).

http://dx.doi.org/10.1016/j.autcon.2017.03.003
0926-5805/

heart rate measurements, which have been used previously for fatigue monitoring and workload assessment [8,16–18]. Specifically, this paper focuses on monitoring thermoregulatory changes that occur during a simulated construction task and compares the accuracy of monitoring thermoregulation to monitoring heart rate for the purpose of assessing physical fatigue. The rest of the paper is organized as follows. Section 2 provides an overview on fatigue, fatigue measurement techniques and a background on human thermoregulation system. Section 3 describes the methodology for the experiment, sensors and sensing systems used, experimental procedures as well as the methods used in data analysis. Section 4 presents the results and explains the findings. Section 5 includes a discussion around the results, the limitations of this study, directions for future research and how the results could impact the field of construction safety. Section 6 concludes the paper.

2. Background and overview of related work

2.1. Methods for measuring fatigue

Fatigue refers to loss of efficiency or disinclination towards any kind of effort, yet it does not have a single definite state [19]. Although some support a unidimensional characterization of fatigue [20], it is usually described as physical fatigue and mental fatigue [19]. Mental fatigue results from prolonged periods of cognitive activity and leads to decrement in cognitive and behavioral performance [21,22]. Physical fatigue results from activities that require physical effort and is defined as the reduction in capacity to perform physical work [23]. Mental fatigue has been shown to impair physical performance [24]. However, light physical exertion seems to improve mental performance and heavy physical exertion leads to decrement in mental performance [25], suggesting a complex relation between physical and mental fatigue. Early attempts at quantifying fatigue involved different assessment scales that relied on subjective answers to a fixed set of questions relating to physical and mental fatigue [26,27]. Several construction related studies have also utilized different subjective feedback scales and questionnaires for assessing fatigue or workload [2,15,28–30]. There is no universally accepted standard for fatigue assessment and different studies have utilized different scales for fatigue assessment [28]. There are also expectation discrepancies caused between how one does feel and how one thinks one should feel, a problem inherent in subjective scales to assess fatigue [31]. Furthermore, collecting subjective feedback is cumbersome and not practical on construction sites, highlighting a need for methods that can continuously monitor fatigue with minimal intrusion to regular construction activities.

In industries that require workers to be mentally vigilant, Psychomotor Vigilance Test (PVT) has been utilized to test the mental alertness of workers. PVT is a standard reaction time test, which has been utilized to monitor alertness of workers in various occupations, such as airport luggage screening [32], long distance driving [33], and nurses working long shifts [34]. Electroencephalogram (EEG) has also been utilized to assess mental fatigue in knowledge workers performing mental tasks [35], in long distance drivers [36,37], and athletes performing exercise in hot environments [38]. EEG has also been utilized to assess mental workload changes in construction workers during installation tasks requiring participants to climb a ladder, select proper nut and fastening the nut to a bolt [39]. Other sensors such as electrooculogram (EOG) have been used to monitor fatigue in drivers [40], and Skin Conductance Response (SCR) has been used to evaluate changes in mental workload during memorization task [41]. These previous studies in various fields have studied changes in mental alertness during tasks requiring mental focus. In the present study, both PVT and EEG are utilized to track declines in mental alertness during a physical activity, which does not require high level of mental focus in an attempt to study the relations between physical and mental fatigue development during construction work.

In industries that require workers to perform repetitive tasks using specific muscle groups, such as the manufacturing industry, localized muscular fatigue has been studied using surface Electromyography (sEMG). For example, sEMG has been used to monitor shoulder muscle fatigue in sewing machine operators [42], pillar drill operators [43] and during overhead drilling work [44]. In addition, sEMG has been used to monitor forearm muscular load in automobile assembly workers [45] and to monitor arm-shoulder fatigue during a nail hammering task [46,47]. Unlike the manufacturing industry, construction work also involves non-repetitive tasks and utilize multiple muscle groups [48], therefore the present study attempts to monitor overall physical fatigue in construction workers rather than localized muscular fatigue. However, overall physical fatigue is more complex than localized muscle fatigue; overall physical fatigue is difficult to quantify as it results from the interactions between local (muscular) and central factors (cardiovascular, metabolic, thermoregulatory changes, etc.) [49]. Previous studies have focused on physical workload monitoring of workers, mostly using heart rate [8,16–18]. A previous study, utilizing physiological measurements of heart rate and oxygen uptake on construction workers, showed that 20% to 40% of construction workers routinely exceed physical thresholds in the published guidelines [8]. Another study, using heart rate and oxygen consumption, showed that the energy expenditure of bar fixing tasks was more than bar bending tasks in a hot environment [16]. Recovery time after working to exhaustion in a hot environment was determined for rebar workers using heart rate, blood pressure and subjective ratings of fatigue [30]. However, several physiological and behavioral factors (e.g., relative body weight, smoking, etc.) influence the heart rate even for roughly equivalent tasks [50], making heart rate monitoring insufficient by itself for reliable monitoring of fatigue. For example, level of physical fitness [51], mentally stressful situations [52], energy drinks intake [53], cigarette smoking [54] and alcohol consumption [55] result in changes of heart rate. In addition, the day to day variability in heart rate limits its clinical usefulness and these fluctuations require comparisons with other physiological changes (e.g., thermoregulatory changes, metabolic changes etc.) to make a more meaningful use of heart rate monitoring for detecting physical overload [56]. Thermoregulatory changes have been linked with the development of fatigue during cycling exercise [57,58]. The present study uses monitoring of heart rate, thermoregulatory changes and subjective ratings of fatigue in order to study the development of physical fatigue. The present study also compares the usefulness of monitoring heart rate and monitoring thermoregulatory changes for the purpose of evaluating physical fatigue.

The recent advances in wearable sensing and computing have helped develop novel methods that can improve safety and health of construction workers. Several studies relating to workload assessment and physiological demands during work have also been conducted under different construction activities and environmental conditions [8,16,59–63]. An early warning system for monitoring heat stress in construction workers has been developed based on environmental and physiological monitoring data [2]. Location sensing and Physiological Status Monitoring (PSM) have been utilized for monitoring ergonomically safe and unsafe behaviors during construction activities [9]. PSM has also been utilized for analyzing the physical strain-productivity relation for construction tasks [64] and physiological condition monitoring of construction workers [59]. These previous studies have utilized heart rate monitoring and other physiological (energy expenditure, oxygen consumption, respiration rate etc.) and environmental information (temperature, humidity etc.) but have not yet investigated thermoregulatory changes that can occur during construction activities.

2.2. Background on human thermoregulatory system

Human thermoregulatory system maintains the core body temperature when exposed to conditions affecting thermal homeostasis. Vasocontraction and vasodilation are the primary mechanisms that modify the blood circulation to the cutaneous vessels by either constricting or dilating the blood vessels [65,66]. During physical exercise, the skin blood flow and hence skin temperature rises to effectively transfer the metabolic heat produced [67]. However, the rise in the skin temperature is not uniform during thermoregulation, and depends on several factors, such as external temperature, mode of activity and activity intensity, which determine the overall heat debt of the body [68–70]. In addition to the thermoregulatory changes, non-thermoregulatory changes in skin blood flow occur during a physical activity to redirect the blood flow towards the working muscles [71]. In other words, there is a need for cutaneous vasoconstriction to redirect the blood flow to the muscles, as well as, a need for cutaneous vasodilation to dissipate the metabolic heat produced, which results in an inherit competition on the control of skin blood flow during physical work [71]. There are several methods for measuring skin blood flow, including photoelectric plethysmography, venous occlusion plethysmography, Doppler ultrasound, impedance and radioactive isotopes [72–74]. However, these methods have many limitations that make them inapplicable at construction sites. These limitations include: the need for highly precise positioning of these devices, requiring participants to maintain low level of physical activity or to avoid motion altogether to prevent measurement errors [75], requiring injections of radioactive isotopes [72], and time consuming procedures [76]. Monitoring skin temperature provides an alternative measure of skin blood flow [76,77], which is achieved, in the present study, by using non-contact infrared temperature sensors.

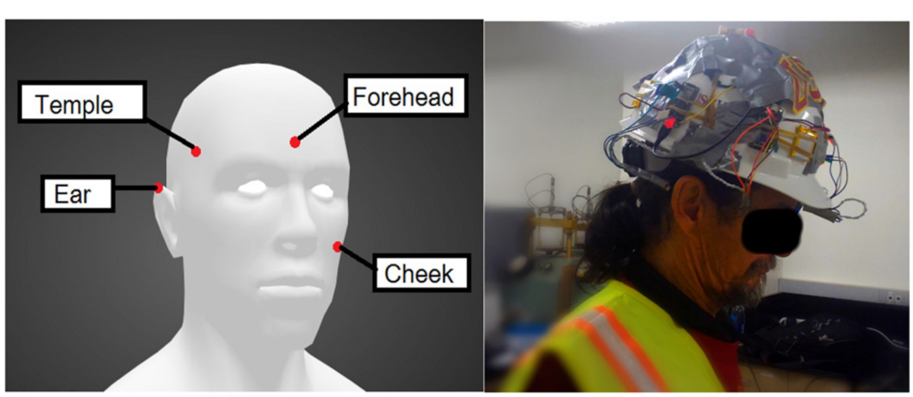
3. Methods

To test if human thermoregulatory changes could be used for assessing fatigue buildup, we developed a sensing system, consisting of infrared sensors attached to a construction safety helmet, collecting skin temperature from four locations on human face, along with heart rate and brainwave signal monitoring. We have collected physiological data from 12 construction workers in an experiment, in which we simulated a material handling task, for which the participants carried 15 kg-sandbags between pick up and drop off locations (10 m distance) in 200 trials. Finally, several supervised machine learning algorithms are tested on the collected data to explore the applicability of the monitored variables for fatigue predictions. The details of the sensors, the sensing system, experimental protocol and design, as well as the details about the data analysis are presented in this section.

3.1. Sensors and sensing systems

In order to monitor the physiological changes during the development of fatigue, a heart rate monitor, an EEG sensor and a construction safety helmet, fitted with four infrared temperature sensors, are used in a simulated construction activity with 12 participants. Garmin vivofit, a commercially available fitness tracking wristband bundled with a chest worn heart rate monitor [78], was used for recording the changes in the heart rate. The chest worn heart rate monitor transmits the sensor data to vivofit, which acts as a data logger. The data is later synced to Garmin's servers and can be downloaded as raw heart rate signals. A commercially available EEG sensor, Neurosky Mindwave [79] bundled with NeuroExperimenter software [80], was used for recording different frequencies of brainwave signals. The Neurosky Mindwave uses a single dry electrode in the forehead and can be worn under a construction safety helmet with very little discomfort. In addition, a construction safety helmet, fitted with four non-contact infrared temperature sensors (MLX90614), connected to a data logger (Adalogger M0), was used to monitor the thermoregulatory changes. In addition to being non-contact, infrared temperature sensors are highly reliable, and have a quicker response time than contact based temperature sensors, such as thermistors for monitoring skin temperatures [81]. The temperature sensors were placed approximately 1 cm away from the skin surface. The temperature monitoring sites (i.e., forehead, temple, ear and cheek) are shown in Fig. 1. The facial region was selected for monitoring thermoregulation as consists of several vascular territories [82], does not contain working muscle groups that are engaged during construction work, and is not covered by clothing or protective equipment making it an ideal location for monitoring thermoregulatory changes using infrared thermography.

Borg's Rating of Perceived Exertion (RPE) was used to collect the participants' perceived level of physical fatigue every 10 trials. The RPE scale is a linear scale, from 6 to 20, with descriptions ranging from “No exertion at all” to “Maximal exertion,” respectively. The RPE scale was proposed by G. Borg as an attempt to quantify subjective symptoms of how people feel and how difficult they perceive their work to be [84], and has been widely used as a valid tool to monitor the collective feedback of physiological, psychological and situational factors that enable an individual to rate how easy or difficult a task is and how tired they feel while performing the tasks [85]. Verbal anchors were added to the RPE scale to enable participants to gauge their level of exertion based on the descriptions suggested by the Center for Disease Control and Prevention (CDC) [86] and is shown in Table 1. A 5-min mobile phone version of the Psychomotor Vigilance Task (PVT) [87] was used every 50 trials to collect information relating to level of mental alertness in participants. The PVT test is a standard reaction time test to assess mental alertness and has been previously used in assessing mental alertness in many fields, such as train operations [88], luggage screening [32], mining [89], nursing [90] etc. In addition, personal information (i.e., participants' age, weight, height, ethnicity, gender, cigarettes smoked per day and years worked as manual labor) was collected during the experiment.



(a) (b)

Fig. 1. a) Skin temperature monitoring sites on the face, figure modified from [83]; b) A participant wearing the helmet.

Table 1
Borg's RPE scale along with verbal anchors and the level of fatigue based on reported RPE.

RPE	Level of exertion	Verbal anchors	Fatigue level
6	No exertion	I am not tired; this is similar to resting	1- Low
7			
7.5	Extremely Light		
8		I am not tired; this is similar to walking	
9	Very Light		
10			
11	Light	I feel fine to continue	
12			2- Medium
13	Somewhat hard		
14		I am getting tired, but I can continue	
15	Hard (heavy)		3- High
16			
17	Very hard	I am very tired; I have to push myself to continue	4- Very High
18			
19	Extremely hard	This is one of the hardest things I have done	
20	Maximal exertion		

3.2. Experiment protocol

In order to study the feasibility of detecting fatigue by monitoring thermoregulatory changes, using our proposed sensing methodology, we adopted a previously developed experimental protocol by Fang et al. [15] with some modifications. The protocol consisted of a manual material handling task, a common construction activity, performed in this study using an experimental platform. 15 kg sandbags were used as it was previously found that construction workers handled objects around 15 kg for over an hour during a typical workday [15]. The supporting platform consisted of a material pick up location, material drop off location, and a walking platform, with four alternating strips designated as the "danger zone" fitted with warning lights sensors to detect errors as shown in Fig. 2 and Fig. 3. For the purposes of this experiment, a trial is defined as lifting one sandbag from the pick-up location and moving it to the drop off location and returning back empty handed. The white or black strips in the danger zone are randomly assigned as the "hazardous strip" during each trial and are indicated by the warning lights alongside the strips. Sensors alongside the strips detect when participants step on the hazardous strip and record it as an error. Participants are required to avoid stepping in the hazardous strip as indicated by the warning lights while passing through the danger zone. This requires the participants to remain alert during the experiment, and the number of errors made provide a way of monitoring changes in mental alertness with the development of fatigue. The pick-up and drop off locations were switched once all the sandbags were accumulated on one location (a total of 6 sandbags were used). The experiment consisted of each participant performing 200 trials. The total experiment took about 2.5 h for each participant.

The modifications to the platform in our study included the types of errors recorded by the platform and use of an alternate type of sensor for detecting the errors. Although the types of errors were modified due to alternate sensors used, the errors reflect the measurement of loss in perception and motor control as intended in the previous study by Fang et al. [15]. Two types of errors were recorded during the experiment. Error type A corresponds to stepping partially on the border of the hazardous strip, which is adjacent to a safe strip. Error type B corresponds to stepping on the border of hazardous strip, which is not adjacent to a safe strip. The errors are illustrated in Fig. 4 when black strip is designated as the hazardous strip. Error type A could happen due to the failure of stepping completely inside the safe strip because of a difficulty in motor control induced by fatigue. It could occur when a participant recognizes the safe strip but is unable to precisely control his step [15]. Error type B could happen due to lack of vigilance and failure to recognize hazard as indicated by the warning lights and reflects a decline in perception [15]. Additional reason for separating the errors into Type A and Type B is because Error Type A could be affected by the shoe sizes of the participants, while Error Type B would not be affected by the shoe sizes. It is possible that a participant makes both Type A and Type B errors in the same trial and if this is the case, both errors were recorded by the platform. The errors were recorded while participants walked either carrying the sandbag or while they returned empty handed. Infrared distance sensors were used to detect where participants stepped.

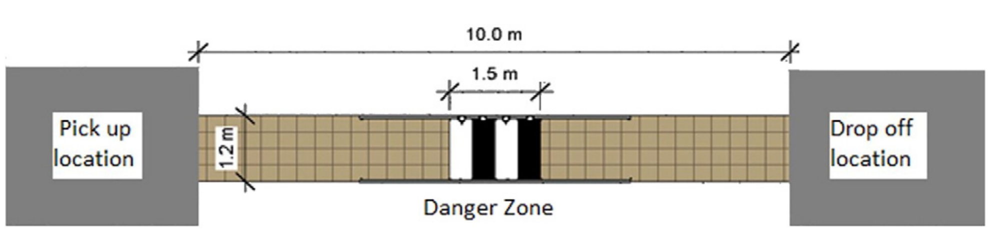


Fig. 2. Schematic design of the supporting platform (adapted from [15]).

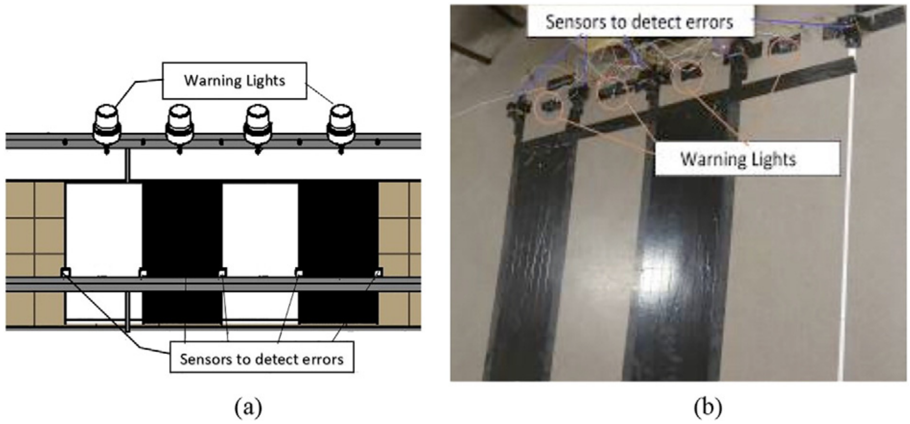


Fig. 3. a) Schematic design of the danger zone; b) Danger zone implemented in the experiment.

3.3. Experimental procedure

The experiment protocol was reviewed and approved by the Institutional Review Board at the University of Southern California. In order to minimize risks to the participants, the inclusion criteria for participants, were to be 18 years or older and to be currently working in construction and performing physical work. A total of 12 male construction workers were recruited for the experiment. The experiment was conducted during the summer months of May and June 2016 at the University of Southern California in Los Angeles. The experiment was conducted in an indoor location. Participants were explained the experiment protocol, the RPE scale, the PVT test and written consent was obtained before starting the experiment.

Once the consent was received, the participants were then asked to wear all the sensors and remained at rest for the first 20 min of the experiment while their baseline heart rate, skin temperatures and EEG waves were recorded. The resting period also allowed the participants to get acclimated to the environment and ensure that the participants started the experiment from a state of rest. While resting, the participants were asked to take the PVT test. Personal information was also verbally collected and recorded during the resting period. After the resting period, the participants started the material handling task, providing their RPE feedback verbally, every 10 trials. The reported RPE was recorded by the research team along with timestamps of when the RPE was reported. The participants took a short break of approximately 5 min every 50 trials and took the PVT test during the break. The errors made by the participants were recorded by the supporting platform, which recorded the timestamp of each type error separately. Ten participants performed the required 200 trials, one of the participants performed 190 trials and stopped due to discomfort (back pain) and one of the participants voluntarily performed 220 trials. The demographic characteristics of the 12 participants are shown in Table 2.

3.4. Data analysis

3.4.1. Data preprocessing

The collected sensor signals included heart rate (bpm) (every 15 s), skin temperatures (every second with a resolution of 0.01 °C) and EEG waves (every second). Sensor data from all of the sensors were preprocessed using a third order one-dimensional median filter [91] and the Savitzky-Golay filter [92] to remove the large spikes in the sensor signals. Then a moving average filter [91] was applied to smooth the sensor signals and to remove the noise. The signals were visually assessed to ensure the noise was removed without any loss of major trends in the signal data. Sensor signals from the infrared sensors, heart rate and Beta1 channel from the EEG sensor, before and after applying the filters are shown in Fig. 5 or one of the participants (#5). Several jumps in sensor signals were observed in the signals due to movement of the sensors caused by participants trying to wipe off sweat from their face or due to the helmet sliding from its position. Such jumps were not filtered out as they are likely to occur if similar wearable sensors were to be used at construction sites. After filtering the sensor signals, the signals were synchronized and several features (explained below) were extracted from the sensor data.

The sensor signals in Fig. 5(b) reflect the thermoregulatory changes that occur during physical work. The first 1200 s (20 min) is relatively stable because the participant was at rest. Once the participant starts physical work, a gradual drop in the temperature is observed. An increase in the temperature is observed when the participant stops the physical activity after each 50 trials (5 min break), followed by drop in

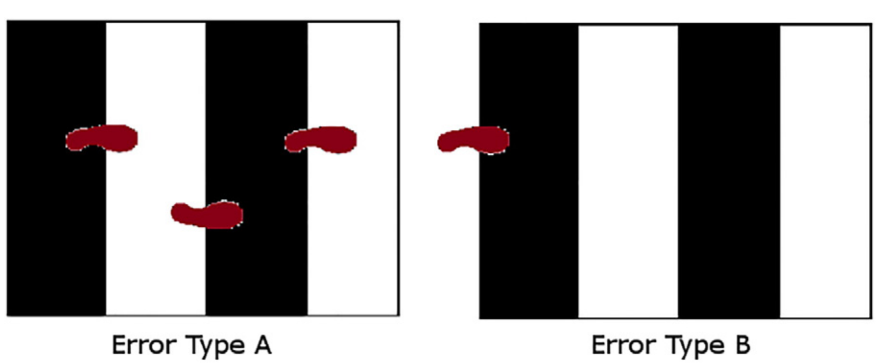


Fig. 4. Illustration of two different types of errors recorded by the experiment platform. The black strip is designated as the hazardous strip in this figure.

Table 2
Demographic characteristics of participants.

	Age	Weight (kg)	Height (cm)	Years worked in construction	Ethnicity
Range	18–60	66–98	163–191	1–30	Caucasian (2)
Mean	43.8	79.6	176.3	11.6	Hispanic (5)
Standard deviation	15.2	9.9	8.5	7.8	African American (5)

temperature as he resumes the physical activity. This can be explained by how blood circulation changes during physical activity. At the onset of the physical activity, cutaneous vasoconstriction occurs to redirect the blood flow to the working muscles, and lowers the skin blood flow and causes the temperature to drop [67,71]. Later, as more metabolic heat is accumulated in the body, cutaneous vasodilation increases the blood flow to the skin to raise the skin temperature and transfers the metabolic heat to the external environment [67,71]. Previous studies that monitored thermoregulation during exercise also reported an initial drop during exercise followed by an increase in the skin temperature immediately after the exercise [93,94]. The variations in the heart rate in Fig. 5(c) also reflect the physical activity performed by the participants. In our experiments, we observed an increase in the heart rate when the participant performs physical work, and a drop in heart rate when the participant paused after each 50 trials. This is because the heart rate is correlated with the intensity of the physical activity [95].

3.4.2. Feature extraction

We studied the feasibility of wearable sensors for monitoring fatigue and compared heart rate monitoring to monitoring thermoregulation. Average skin temperature was calculated from the four sensor signals and used as a representative signal. The level of fatigue as reported by the participants is used as the label for each 2-min interval (every 10 trial). Several features were extracted from the average temperature data by looking at a buffer of 2 min prior to the times where the levels of fatigue were reported. The features extracted from each buffer included the minimum and maximum temperature, average temperature, standard deviation, the largest temperature drop, minimum and maximum rates of change, the minimum temperature reached so far, and the difference between minimum temperature in the buffer and the minimum temperature reached so far. Using the heart rate signals, minimum heart rate, maximum heart rate, average heart rate and standard deviation were calculated from each buffer. Duration of work (i.e., time

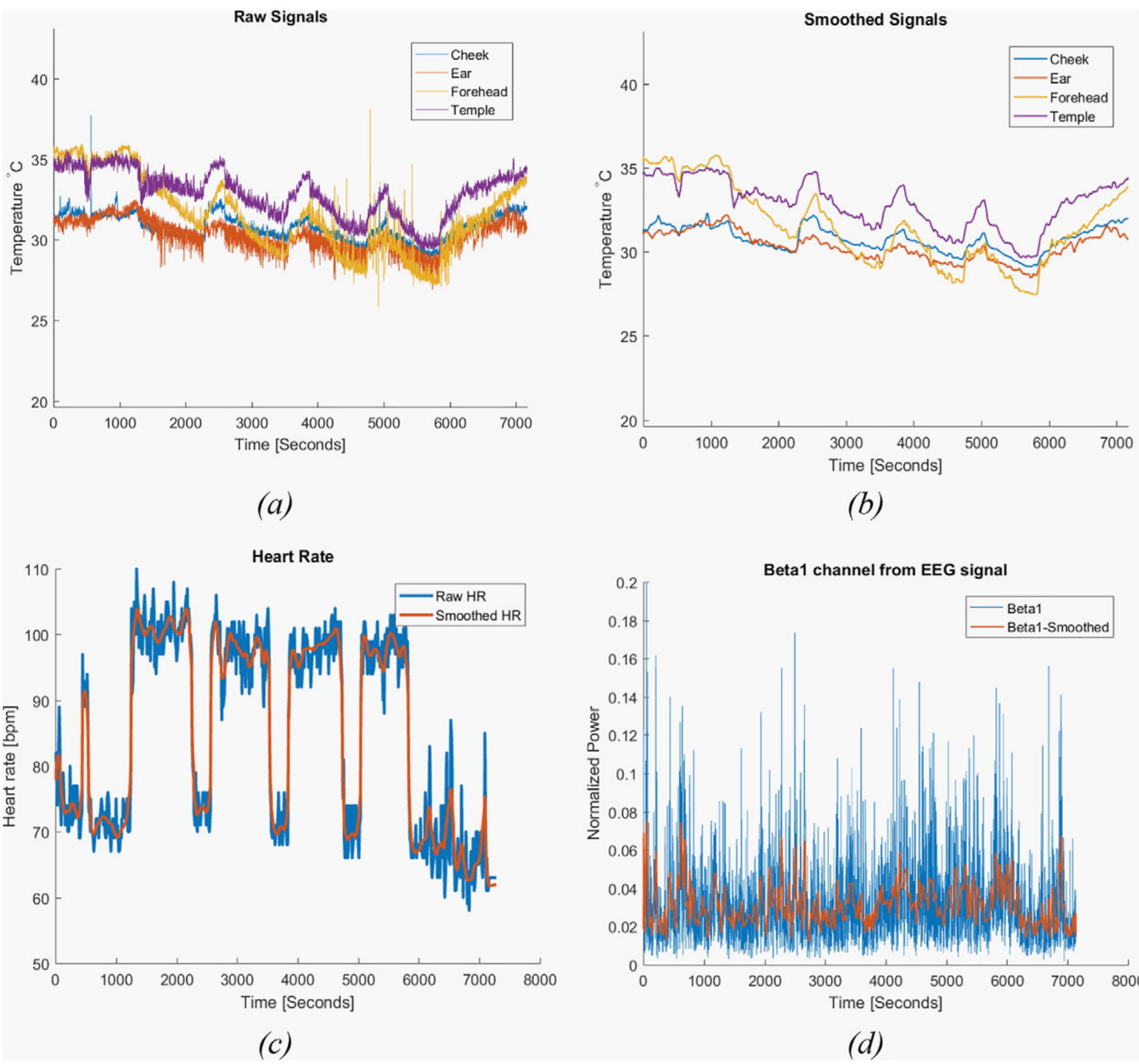


Fig. 5. For participant #5, a) Raw sensor signals from temperature sensors; b) Sensor signals from temperature sensor after preprocessing; c) Heart rate before and after preprocessing; d) Beta1 channel from EEG sensor before and after smoothing.

since start of the experiment), and personal features from the participants (i.e., ethnicity, age, weight, height, BMI, cigarettes smoked per day, years worked as manual labor) were included as features to be used as input to the classification algorithms. A total of 21 features were extracted, which included 7 personal features, 9 features from the temperature signals, 4 features from the heart rate signal and the duration of work. The features were obtained from each participant at the intervals of 10 trials (0 and 200 inclusive), except one participant, who performed 20 more trials and another participant who did not perform the last 10 trials. The dataset consisted a total of 253 sets of features together with the corresponding fatigue levels (RPE).

3.4.3. Classification

Different well-established generative and deterministic classification algorithms were tested to select the classification algorithm that provides the highest accuracy. The tested algorithms included decision trees, boosted trees, and Support Vector Machines (SVM) with different kernel functions (linear, quadratic, cubic, and Gaussian). The decision tree algorithm was used with maximum number of splits as 100 (complex trees), 20 (medium trees) and 4 (simple trees). The boosted trees algorithm was used with medium trees as base learners and bagged trees as an ensemble of complex trees. SVM algorithm uses a probabilistic binary linear classifier to learn the structure in the data and the kernel functions transform the features into high-dimensional spaces to improve the accuracy. The linear SVM uses the original features of the data. The quadratic and cubic SVM take each feature dimension into their squared and cubic values, respectively. Gaussian SVM uses a radial basis function to transform the features. The details of these classification algorithms and the process of fine tuning their hyper parameters are not discussed here as they can be found in several machine learning resources [96]. In a 10-fold cross validation, the data set is randomly divided into 10 batches and the classification algorithm uses each batch as a validation data set and the combined remaining sets as the training data set in 10 iterations. The reported accuracy is the average accuracy of the 10 iterations.

The overall classification of the tested algorithms is shown in Table 3. The boosted trees algorithm outperforms all the tested algorithms and was selected for further analysis. The Ensemble method used was Adaptive Boosting with medium decision trees as weak learners, the maximum number of splits was 20, the maximum number of learners was set as 30 and the learning rate was set at 0.1. The adaptive boosting for the decision tree uses Eq. (1) to combine the predictions from trained trees to predict the outcome. Each of the decision trees uses Eq. (2) as the objective function in their training process.

$$\hat{y}_i = \sum_{k=1}^{K} d_n^{(t)} f_k(x_i), f_k \in F \tag{1}$$

where, $d_n^{(t)}$ is the weight of observation n at step t, and $f_k(x_i)$ is the prediction from each tree

$$\sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{2}$$

Table 3
Classification accuracies of each tested algorithm.

Algorithm	Classification accuracy
Complex tree	74.30%
Medium tree	72.70%
Simple tree	62.80%
Linear SVM	73.90%
Quadratic SVM	79.80%
Cubic SVM	77.90%
Gaussian SVM	77.10%
Boosted trees	82.60%
Bagged trees	79.10%
RUSBoosted trees	80.60%

where, $\sum_{i=1}^{n} l(y_i, \hat{y}_i)$ is the training loss and $\sum_{k=1}^{K} \Omega(f_k)$ is the complexity of the trees.

4. Analysis and results

Boosted trees that used all the extracted features as inputs had the highest classification accuracy of 82.6% among the tested supervised learning methods. The confusion matrix is shown in Fig. 6a. An interesting observation from the results is that all the incorrectly classified points were adjacent to the true class, i.e., a true class of label 4 (very high fatigue) was misclassified as label 3 (high fatigue) but not as low levels of fatigue, indicating that the extracted features were related to the level of fatigue. Although there is room for improvement, the high accuracy obtained demonstrates the feasibility of using wearable sensors to monitor fatigue.

In order to compare the effectiveness of monitoring heart rate and monitoring thermoregulation changes, boosted tree classifiers were trained by excluding the features extracted from the heart rate monitor, and from the temperature sensors, respectively. The duration of work is related to the level of fatigue participants experienced (i.e., as participants complete more trials they are likely to get more tired) because of the repetitive nature of the material handling task. Although the duration of work is a useful feature, it was excluded at this stage in order to compare the prediction accuracies solely based on the sensor signals and personal factors that could influence the heart rate and thermoregulation changes. The classification accuracy using the personal features and the features from both the heart rate and temperature sensors was 72% (Fig. 6b). The classification accuracy using personal features and features extracted only from the heart rate data was 59% (Fig. 6c). The classification accuracy using personal features and features only from the temperature sensors was 68% (Fig. 6d). The results indicate that monitoring thermoregulation might be a better alternative compared to monitoring heart rate for the purpose of predicting fatigue. Combining the information from both types of sensors results in only a slightly better accuracy as we have more information regarding the physiological changes during the activity. Removing the personal features and using only the features from both heart rate and temperature sensors resulted in a classification accuracy of 57%. The 15% decrease in accuracy from 72% shows that personal features are important in order to account for physiological differences among workers.

In order to identify the best site on the face for monitoring thermoregulation among the sites studied, boosted tree classifiers were trained with 10-fold cross validation using the features extracted from a single temperature sensor instead of the features extracted from the calculated average signal used in the previous step. Duration of work and the features from the heart rate data were not included as features in order to compare the prediction accuracy based on only personal factors and the temperature sensor data. The prediction accuracies from each of the sensors were compared and are reported in Table 4.

The features extracted only from the temperature sensor located at the temple achieved the highest accuracy of 79.4%. It is important to note that the accuracy achieved using only the sensors data from the temple or the forehead was higher than the accuracy achieved by using the averaged data. Equally important, all of the sensor points yielded better results than the average received by using heart rate and personal factors (59%).

The reaction times from the PVT tests (recorded every 50 trials) did not show any signs of mental fatigue in the collected data (Fig. 7). The number of type A errors and type B errors made by the participants in each interval of 50 trials also did not show any signs of mental fatigue, and is shown in Fig. 8. Please note that some Error Type A data is missing for the participants 3 and 5 due to failure of the sensing system during the experiment. The number of errors

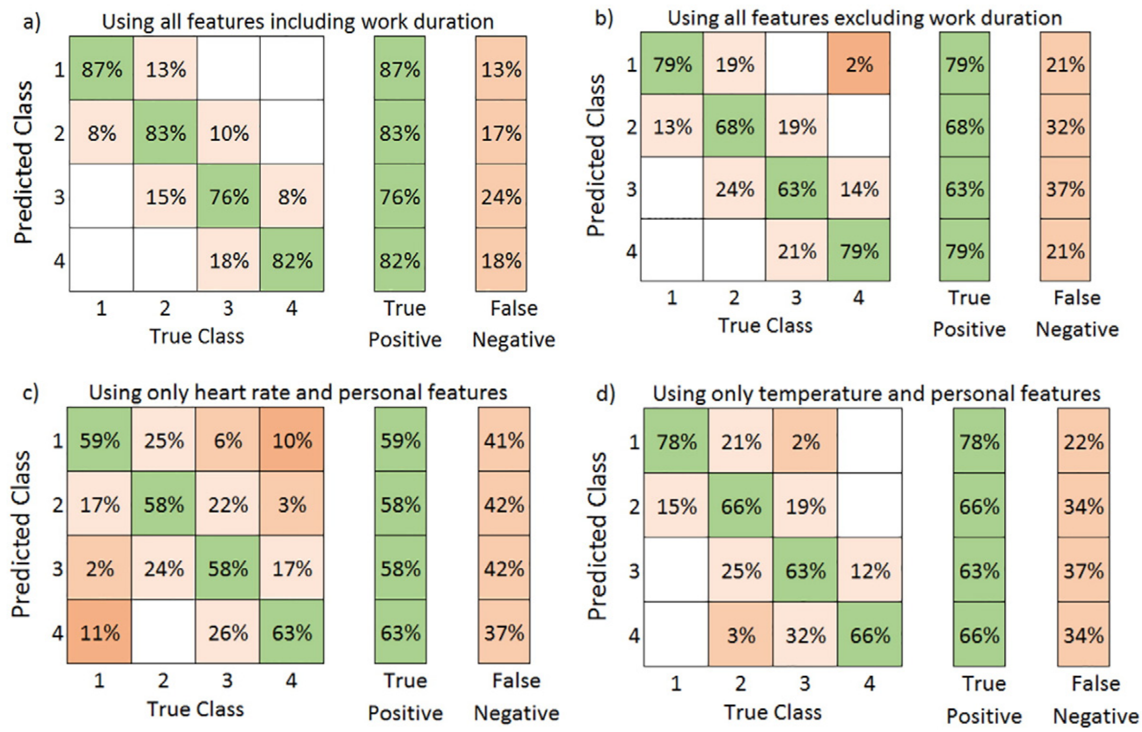


Fig. 6. Confusion Matrices: a) using all features; b) using all features excluding work duration; c) using only heart rate and personal features; d) using only temperature and personal features.

made by the participants was expected to rise with the development of the mental fatigue.

The EEG signals collected during the experiment were also checked for indications of fatigue development. An interesting observation was that the ratio of (Alpha1 + Theta) / Beta1 waves showed some increase along with the development of physical fatigue as indicated by increase in RPE. The frequency bands of 4–7 Hz corresponds to Theta, 8–9 Hz corresponds to Alpha1, and 13–17 Hz corresponds to Beta1 waves [97]. The ratio (Alpha + Theta) / Beta waves were used previously as a measure to monitor fatigue in drivers [36]. The increase was not consistent among all the participants, however drops were observed in the ratio during the period when the participants were taking the PVT test and they were mentally focused. There was no significant development of mental fatigue during the study as seen from the number of errors made by the participants and the reaction times from PVT tests, and no consistent changes were observed in the EEG signal among the participants either.

5. Discussion

The study attempted to investigate both physical and mental fatigue. Heart rate, temperature and the RPE scale were used to monitor physical fatigue, and EEG, PVT and the errors made by participants were used to monitor mental fatigue. However, none of the participants developed any sign of mental fatigue during the study. Therefore, only physical fatigue could be assessed in the study. The results show that monitoring changes in the thermoregulation system can provide more useful information in predicting physical fatigue compared to monitoring heart rate. In practical terms, monitoring thermoregulation is also more preferable and feasible in terms of workers' comfort than monitoring heart rate for improving construction site safety. The non-contact sensors can be fitted to a safety helmet, which is required to be worn as part of personal protective equipment at a construction site, therefore does not require additional equipment to be worn by the workers. All of the sensors, data loggers and batteries added approximately 110 g to the weight of the helmet. For a real world application, the sensors and data loggers would need to be fastened more securely to the helmet, and the weight could be further reduced by using a single battery instead of four batteries used in the study. The results also show that the temple is the most suitable location among the studied sites for monitoring thermoregulation to predict physical fatigue. It is also the most practical location considering the nature of construction work. Cheek is relatively far from the helmet, which makes it difficult to attach sensors for practical use and also introduced more noise in the signals due to sensor motion. Ear shapes differ from one person to another and long hair can interfere with the sensor. During the experiment it was observed that the participants wanted to wipe sweat off of their forehead repeatedly. Although they were very careful not to move the sensors because of the instructions provided, this would result in additional noise in the sensor signals due to sensor movement if used on a real construction site. From a practical perspective, sweating has a cooling effect on the skin and should be taken into consideration as workers can sweat during work. Skin temperature is a result of skin blood flow, muscular activity, and sweating [98]. Previous studies reported slightly lower temperature measurements using infrared temperature sensors compared to the contact based sensors under influence of sweating [99]. This is likely to be caused by lower skin emissivity in the presence of sweat [100,101] leading to lower infrared temperature measurements. However, the use of infrared temperature sensors is advantageous over contact based temperature sensors due to their faster response time, their ability to provide more comfortable conditions for workers, and the lower chances of sensors being detached during movement and sweating [102]. Although the impact of

Table 4
Classification accuracy based on individual temperature sensors.

Sensors used	Classification accuracy
Cheek	64.4%
Ear	71.1%
Forehead	76.7%
Temple	79.4%

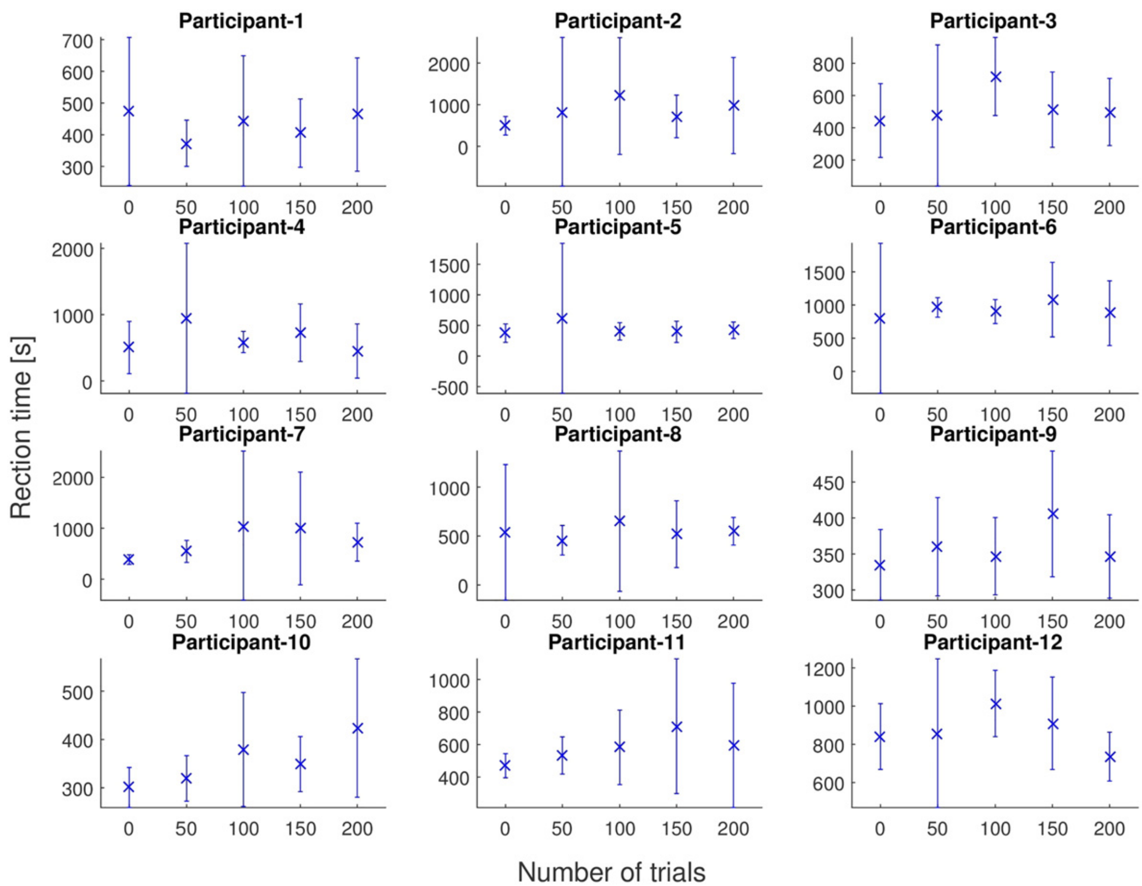


Fig. 7. Mean reaction times from the PVT tests for each participant with corresponding standard deviations shown as error-bars.

sweat cannot be quantified in this study, the infrared temperature measurements include the impact of sweat on skin temperature and therefore, the resulting prediction includes the effect of sweating.

The classification accuracy obtained using data from the temple alone is 20% higher than the classification accuracy obtained using the heart rate data. A possible reason for better classification accuracies based on data from the temple (79%) and forehead (76%) could be the way blood vessels are distributed in human face. The superficial temporal artery is one of the largest arteries in the face and passes through the temple [103]. The temporal artery divides into two major branches, one of which supplies the scalp and another supplies the forehead [103]. The proximity to larger blood vessels could mean that the information from these sites is more closely related to variations in blood flow due to thermoregulatory changes compared to other sites. The approach used for monitoring thermoregulation could supplement the studies involving physiological monitoring of construction workers by providing additional information about physiological changes that occur during construction work.

The results from the PVT test and the number of errors made by the participants did not show any significant changes during the experiment. This indicates that the duration of the experiment was not long enough to cause significant development of mental fatigue. The EEG signals did show some changes corresponding to the participants' level of alertness. Drops observed in (Alpha1 + Theta) / Beta1 ratio during the PVT task where participants were required to remain mentally alert, indicate that the ratio might be potentially useful as a measure of mental fatigue level. This should be investigated in future studies, which last longer in order for significant mental fatigue to be built up. Understanding the development of mental fatigue is also useful for improving construction safety and productivity.

This study successfully demonstrated that infrared temperature sensors could be used for physical fatigue monitoring on construction workers, however it has some limitations. For example, only one type of task (i.e., material handling) was studied. Even though material handling is one of the most physically demanding tasks in construction [15], typical construction work involves different activities. For real life application of a fatigue monitoring system, different types of tasks should be studied. Environmental factors, especially temperature and humidity, affect fatigue significantly. This study was conducted under room temperature. Future studies should be conducted under different environmental conditions. For example, heat stress causes fatigue to build up faster and is one of the problems faced by construction workers in hot climates; monitoring thermoregulation under such conditions using a similar approach could be highly beneficial in ensuring workers' safety.

Another limitation is that the experimental results might not reflect the actual conditions at work as some bias could have been introduced by conducting the experiment, and participants could behave differently when being observed. Conducting the experiment might have introduced bias in the subjective feedback (RPE) from the participants in form of expectation discrepancies between ‘how one feels’ and ‘how one thinks one should feel’ (e.g., Reporting a slightly lower RPE to show they are stronger). In order to reduce the possibilities of this bias, verbal cues were added to the RPE scale as shown in Table 1 to help participants gauge their responses. Furthermore, grouping of the RPE into 4 levels of fatigue as shown in Table 1 reduces the bias caused by the possibility of reporting slightly higher/lower levels of fatigue due to individual differences in understanding of the subjective scale. On the other hand, the sensor measurements are not likely to suffer from the bias that could be introduced by conducting the experiment. Although heart rate could be impacted by behavioral factors such as stress, in

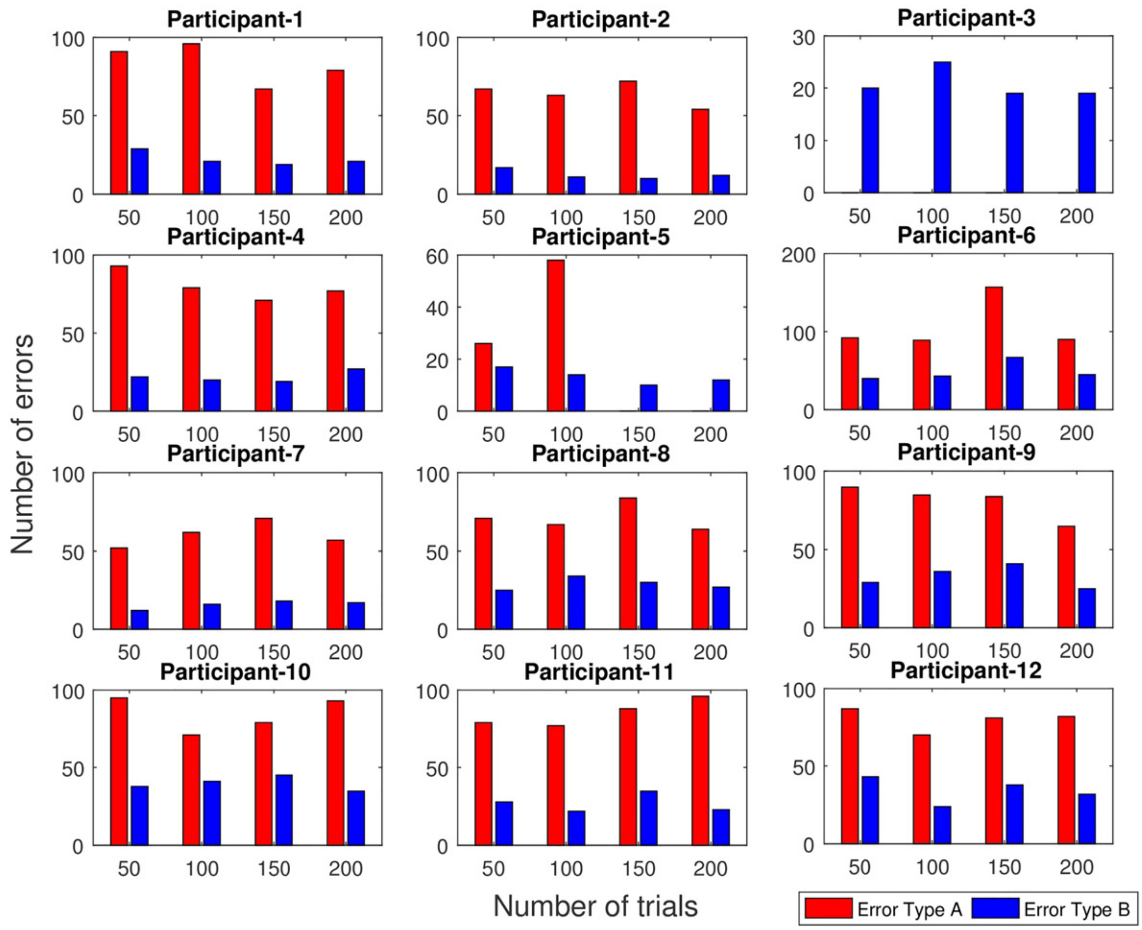


Fig. 8. Type A and B errors made by each participant during the experiment at each 50 trial interval.

this experiment, heart rate and skin blood flow are highly influenced by the physical work and impact from other factors would be very small, if any. Therefore, the possibility of bias in the sensor measurements due to the fact that this was a controlled experiment is not likely.

6. Conclusions

Real time fatigue monitoring of construction workers can enhance construction site safety and help in preventing accidents. In this study, we explored a novel approach for providing real time fatigue information on construction sites. The research objective was to investigate the usefulness of monitoring physiological changes for the purpose of predicting the level of physical fatigue. The study also compared the usefulness of monitoring thermoregulation changes compared to monitoring heart rate and established thermoregulation monitoring sites on the face that are more suitable for a real world application. The study consisted of construction workers performing a simulated construction activity while being monitored using different wearable sensors. Subjective ratings relating to level of physical fatigue was collected periodically during the study. The study affirms that the Boosted tree classifiers can be used to predict fatigue in construction workers using features extracted from the sensor signals. Furthermore, the results show that monitoring thermoregulation can provide more valuable information compared to monitoring heart rate for physical fatigue assessment. The classification accuracy based solely on features extracted from average of skin temperature data was 9% higher than based solely on the heart rate data, and combining information from both sensors resulted in the best accuracy of 82%. The results also show that monitoring thermoregulation from temple can be more useful compared to other studied monitoring sites, the classification accuracy based only on the data from the temple was 79%. This accuracy is significantly higher compared to the classification accuracy based only on the heart rate data (59%). The approach used in this study to monitor thermoregulation could also supplement other construction health and safety studies. The results from this study can also be useful for developing warning systems against high levels of physical fatigue and for designing better work rest schedules in the future to improve workers' safety.

References

[1] International Labor Organization (ILO), Facts of Safety at Work, http://www.ilo.org/wcmsp5/groups/public/—dgreports/—dcomm/documents/publication/wcms_067574.pdf 2005 (accessed July 17, 2016).
[2] W. Yi, A.P.C. Chan, X. Wang, J. Wang, Development of an early-warning system for site work in hot and humid environments: a case study, Autom. Constr. 62 (2015) 101–113, http://dx.doi.org/10.1016/j.autcon.2015.11.003.
[3] Bureau of Labor Statistics, Employment by Major Industry Sector, http://www.bls.gov/emp/ep_table_201.htm 2015 (accessed January 20, 2016).
[4] Bureau of Labor Statistics (BLS), Census of Fatal Occupational Injuries (Final Data): Industry by Event or Exposure, 2016, https://www.bls.gov/iif/oshwc/cfoi/cftb0295.xlsx 2015.
[5] Bureau of Labor Statistics (BLS), Nonfatal Occupational Injuries and Illnesses Requiring Days Away From Work - Table 1, 2015 2016https://www.bls.gov/news.release/pdf/osh2.pdf.
[6] B. Esmaeili, M.R. Hallowell, Diffusion of Safety Innovations in the Construction Industry, 2011http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000499.
[7] A.J.-P. Tixier, M.R. Hallowell, B. Rajagopalan, D. Bowman, Application of machine learning to construction injury prediction, Autom. Constr. 69 (2016) 102–114, http://dx.doi.org/10.1016/j.autcon.2016.05.016.
[8] T.S. Abdelhamid, J.G. Everett, Physiological demands during construction work, J. Constr. Eng. Manag. 128 (2002) 427–437, http://dx.doi.org/10.1061/(ASCE)0733-9364(2002)128:5(427).
[9] T. Cheng, G.C. Migliaccio, J. Teizer, U.C. Gatti, Data fusion of real-time location sensing and physiological status monitoring for ergonomics analysis of construction workers, J. Comput. Civ. Eng. 27 (2012) 320–335, http://dx.doi.org/10.1061/(ASCE)CP.1943-5487.0000222.

[10] M. Zhang, L.A. Murphy, D. Fang, A.J. Caban-Martinez, Influence of fatigue on construction workers' physical and cognitive function, Occup. Med. (Lond.) 65 (2015) 245–250, http://dx.doi.org/10.1093/occmed/kqu215.

[11] P. Parijat, T.E. Lockhart, Effects of lower extremity muscle fatigue on the outcomes of slip-induced falls, Ergonomics 51 (2008) 1873–1884, http://dx.doi.org/10.1080/00140130802567087.

[12] OSHA, Commonly Used Statistics - OSHA, OSHA Website, https://www.osha.gov/oshstats/commonstats.html 2015 (accessed February 9, 2016).

[13] S. Rowlinson, A. Yunyanjia, B. Li, C. Chuanjingju, Management of climatic heat stress risk in construction: a review of practices, methodologies, and future research, Accid. Anal. Prev. 66 (2014) 187–198, http://dx.doi.org/10.1016/j.aap.2013.08.011.

[14] M.R. Hallowell, Worker fatigue, Prof. Saf. 55 (2010) 18 http://search.proquest.com/docview/763614893.

[15] D. Fang, Z. Jiang, M. Zhang, H. Wang, An experimental method to study the effect of fatigue on construction workers' safety performance, Saf. Sci. 73 (2015) 80–91, http://dx.doi.org/10.1016/j.ssci.2014.11.019.

[16] D.P.-L. Wong, J.W.-Y. Chung, A.P.-C. Chan, F.K.-W. Wong, W. Yi, Comparing the physiological and perceptual responses of construction workers (bar benders and bar fixers) in a hot environment, Appl. Ergon. 45 (2014) 1705–1711, http://dx.doi.org/10.1016/j.apergo.2014.06.002.

[17] U.C. Gatti, S. Schneider, G.C. Migliaccio, Physiological condition monitoring of construction workers, Autom. Constr. 44 (2014) 227–233, http://dx.doi.org/10.1016/j.autcon.2014.04.013.

[18] A. Mital, H. Foononi-Fard, M.L. Brown, Physical fatigue in high and very high frequency manual materials handling: perceived exertion and physiological indicators, Hum. Factors J. Hum. Factors Ergon. Soc. 36 (1994) 219–231, http://dx.doi.org/10.1177/001872089403600204.

[19] E. Grandjean, Fatigue in industry, Occup. Environ. Med. 36 (1979) 175–186, http://dx.doi.org/10.1136/oem.36.3.175.

[20] H.J. Michielsen, J. De Vries, G.L. Van Heck, F.J.R. Van de Vijver, K. Sijtsma, Examination of the dimensionality of fatigue, Eur. J. Psychol. Assess. 20 (2004) 39–48, http://dx.doi.org/10.1027/1015-5759.20.1.39.

[21] M.A.S. Boksem, T.F. Meijman, M.M. Lorist, Effects of mental fatigue on attention: an ERP study, Brain Res. Cogn. Brain Res. 25 (2005) 107–116, http://dx.doi.org/10.1016/j.cogbrainres.2005.04.011.

[22] M.A.S. Boksem, M. Tops, Mental fatigue: costs and benefits, Brain Res. Rev. 59 (2008) 125–139, http://dx.doi.org/10.1016/j.brainresrev.2008.07.001.

[23] V.J. Gawron, J. French, D. Funke, An Overview of Fatigue, in: P.A. Hancock, P.A. Desmond (Eds.), Stress, workload, and fatigue, Lawrence Erlbaum Associates Publishers, Mahwah, NJ 2001, pp. 581–595.

[24] S.M. Marcora, W. Staiano, V. Manning, Mental fatigue impairs physical performance in humans, J. Appl. Physiol. 106 (2009) 857–864, http://dx.doi.org/10.1152/japplphysiol.91324.2008.

[25] C.P. Davey, Physical exertion and mental performance, Ergonomics 16 (1973) 595–599, http://dx.doi.org/10.1080/00140137308924550.

[26] K.A. Lee, G. Hicks, G. Nino-Murcia, Validity and reliability of a scale to assess fatigue, Psychiatry Res. 36 (1991) 291–298, http://dx.doi.org/10.1016/0165-1781(91)90027-M.

[27] T. Chalder, G. Berelowitz, T. Pawlikowska, L. Watts, S. Wessely, D. Wright, et al., Development of a fatigue scale, J. Psychosom. Res. 37 (1993) 147–153, http://dx.doi.org/10.1016/0022-3999(93)90081-P.

[28] M. Zhang, E.H. Sparer, L.A. Murphy, J.T. Dennerlein, D. Fang, J.N. Katz, et al., Development and validation of a fatigue assessment scale for U.S. construction workers, Am. J. Ind. Med. 58 (2015) 220–228, http://dx.doi.org/10.1002/ajim.22411.

[29] P. Mitropoulos, B. Memarian, Task Demands in Masonry Work: Sources, Performance Implications, and Management Strategies, 2012http://dx.doi.org/10.1061/(ASCE)CO.1943-7862.0000586.

[30] A.P.C. Chan, W. Yi, D.P. Wong, M.C.H. Yam, D.W.M. Chan, Determining an optimal recovery time for construction rebar workers after working to exhaustion in a hot and humid environment, Build. Environ. 58 (2012) 163–171, http://dx.doi.org/10.1016/j.buildenv.2012.07.006.

[31] L.S. Aaronson, C.S. Teel, V. Cassmeyer, G.B. Neuberger, L. Pallikkathayil, J. Pierce, et al., Defining and measuring fatigue, J. Nurs. Scholarsh. 31 (1999) 45–50, http://dx.doi.org/10.1111/j.1547-5069.1999.tb00420.x.

[32] M. Basner, J. Rubinstein, Fitness for duty: a 3-minute version of the psychomotor vigilance test predicts fatigue-related declines in luggage-screening performance, J. Occup. Environ. Med. 53 (2011) 1146–1154, http://dx.doi.org/10.1097/JOM.0b013e31822b8356.

[33] Y.Y. Tan, S.T. Lin, F. Tey, Development of Fatigue-Associated Measurement to Determine Fitness for Duty and Monitor Driving Performance, Springer, Berlin, Heidelberg, 2013 608–617, http://dx.doi.org/10.1007/978-3-642-39454-6_65.

[34] J. Geiger-Brown, V.E. Rogers, A.M. Trinkoff, R.L. Kane, R.B. Bausell, S.M. Scharf, Sleep, sleepiness, fatigue, and performance of 12-hour-shift nurses, Chronobiol. Int. 29 (2012) 211–219, http://dx.doi.org/10.3109/07420528.2011.645752.

[35] O.G. Okogbaa, R.L. Shell, D. Filipusic, On the investigation of the neurophysiological correlates of knowledge worker mental fatigue using the EEG signal, Appl. Ergon. 25 (1994) 355–365, http://dx.doi.org/10.1016/0003-6870(94)90054-X.

[36] B.T. Jap, S. Lal, P. Fischer, E. Bekiaris, Using EEG spectral components to assess algorithms for detecting fatigue, Expert Syst. Appl. 36 (2009) 2352–2359, http://dx.doi.org/10.1016/j.eswa.2007.12.043.

[37] S.K.L. Lal, A. Craig, P. Boord, L. Kirkup, H. Nguyen, Development of an algorithm for an EEG-based driver fatigue countermeasure, J. Saf. Res. 34 (2003) 321–328, http://dx.doi.org/10.1016/S0022-4375(03)00027-6.

[38] B. Nielsen, T. Hyldig, F. Bidstrup, J. González-Alonso, G.R.J. Christoffersen, Brain activity and fatigue during prolonged exercise in the heat, Pflugers Arch. 442 (2001) 41–48, http://dx.doi.org/10.1007/s004240100515.

[39] J. Chen, X. Song, Z. Lin, Revealing the "invisible gorilla" in construction: estimating construction safety through mental workload assessment, Autom. Constr. 63 (2016) 173–183, http://dx.doi.org/10.1016/j.autcon.2015.12.018.

[40] Thum Chia Chieh, M.M. Mustafa, A. Hussain, S.F. Hendi, B.Y. Majlis, Development of Vehicle Driver Drowsiness Detection System Using Electrooculogram (EOG), 1st Int. Conf. Comput. Commun. Signal Process. with Spec. Track Biomed. Eng., IEEE2005, 2005, pp. 165–168, http://dx.doi.org/10.1109/CCSP.2005.4977181.

[41] Y. Shimomura, T. Yoda, K. Sugiura, A. Horiguchi, K. Iwanaga, T. Katsuura, Use of frequency domain analysis of skin conductance for evaluation of mental workload, J. Physiol. Anthropol. 27 (2008) 173–177, http://dx.doi.org/10.2114/jpa2.27.173.

[42] B.R. Jensen, B. Schibye, K. Søgaard, E.B. Simonsen, G. Sjøgaard, Shoulder muscle load and muscle fatigue among industrial sewing-machine operators, Eur. J. Appl. Physiol. Occup. Physiol. 67 (1993) 467–475, http://dx.doi.org/10.1007/BF00376465.

[43] H. Christensen, Muscle activity and fatigue in the shoulder muscles during repetitive work, Eur. J. Appl. Physiol. Occup. Physiol. 54 (1986) 596–601, http://dx.doi.org/10.1007/BF00943347.

[44] D. Sood, M.A. Nussbaum, K. Hager, Fatigue during prolonged intermittent overhead work: reliability of measures and effects of working height, Ergonomics 50 (2007) 497–513, http://dx.doi.org/10.1080/00140130601133800.

[45] G.M. Hägg, J. Öster, S. Byström, Forearm muscular load and wrist angle among automobile assembly line workers in relation to symptoms, Appl. Ergon. 28 (1997) 41–47, http://dx.doi.org/10.1016/S0003-6870(96)00033-6.

[46] J.N. Cote, A.G. Feldman, P.A. Mathieu, M.F. Levin, Effects of fatigue on intermuscular coordination during repetitive hammering, Mot. Control. 12 (2008) 79–92 http://www.ncbi.nlm.nih.gov/pubmed/18483444 (accessed July 27, 2016).

[47] E. Hammarskjöld, K. Harms-Ringdahl, Effect of arm-shoulder fatigue on carpenters at work, Eur. J. Appl. Physiol. Occup. Physiol. 64 (1992) 402–409, http://dx.doi.org/10.1007/BF00625058.

[48] B. Buchholz, V. Paquet, L. Punnett, D. Lee, S. Moir, PATH: a work sampling-based approach to ergonomic job analysis for construction and other non-repetitive work, Appl. Ergon. 27 (1996) 177–187, http://dx.doi.org/10.1016/0003-6870(95)00078-X.

[49] R. Meeusen, P. Watson, H. Hasegawa, B. Roelands, M.F. Piacentini, Central fatigue, Sports Med. 36 (2006) 881–909, http://dx.doi.org/10.2165/00007256-200636100-00006.

[50] M.S. Green, Y. Luz, E. Jucha, M. Cocos, N. Rosenberg, Factors affecting ambulatory heart rate in industrial workers, Ergonomics 29 (1986) 1017–1027, http://dx.doi.org/10.1080/00140138608967215.

[51] R.E. De Meersman, Heart rate variability and aerobic fitness, Am. Heart J. 125 (1993) 726–731, http://dx.doi.org/10.1016/0002-8703(93)90164-5.

[52] M. Pagani, G. Mazzuero, A. Ferrari, D. Liberati, S. Cerutti, D. Vaitl, et al., Sympathovagal interaction during mental stress. A study using spectral analysis of heart rate variability in healthy control subjects and patients with a prior myocardial infarction, Circulation 83 (1991) II43–II51 http://europepmc.org/abstract/med/2009629 (accessed January 24, 2016).

[53] A. Bichler, A. Swenson, M.A. Harris, A combination of caffeine and taurine has no effect on short term memory but induces changes in heart rate and mean arterial blood pressure, Amino Acids 31 (2006) 471–476, http://dx.doi.org/10.1007/s00726-005-0302-x.

[54] I. Barutcu, A.M. Esen, D. Kaya, M. Turkmen, O. Karakaya, M. Melek, et al., Cigarette smoking and heart rate variability: dynamic influence of parasympathetic and sympathetic maneuvers, Ann. Noninvasive Electrocardiol. 10 (2005) 324–329, http://dx.doi.org/10.1111/j.1542-474X.2005.00636.x.

[55] D.J. Stott, S.G. Ball, G.C. Inglis, D.L. Davies, R. Fraser, G.D. Murray, et al., Effects of a single moderate dose of alcohol on blood pressure, heart rate and associated metabolic and endocrine changes, Clin. Sci. 73 (1987) 411–416, http://dx.doi.org/10.1042/cs0730411.

[56] L. Bosquet, S. Merkari, D. Arvisais, A.E. Aubert, Is heart rate a convenient tool to monitor over-reaching? A systematic review of the literature, Br. J. Sports Med. 42 (2008) 709–714, http://dx.doi.org/10.1136/bjsm.2007.042200.

[57] C.R. Abbiss, P.B. Laursen, Models to explain fatigue during prolonged endurance cycling, Sports Med. 35 (2005) 865–898, http://dx.doi.org/10.2165/00007256-200535100-00004.

[58] J. González-Alonso, C. Teller, S.L. Andersen, F.B. Jensen, T. Hyldig, B. Nielsen, Influence of body temperature on the development of fatigue during prolonged exercise in the heat, J. Appl. Physiol. 86 (1999).

[59] U.C. Gatti, S. Schneider, G.C. Migliaccio, Physiological condition monitoring of construction workers, Autom. Constr. 44 (2014) 227–233, http://dx.doi.org/10.1016/j.autcon.2014.04.013.

[60] U. Gatti, G. Migliaccio, S. Schneider, Wearable physiological status monitors for measuring and evaluating workers' physical strain: preliminary validation, Comput. Civ. Eng. 194–201 (2011)http://dx.doi.org/10.1061/41182(416)24.

[61] S. Li, B.B. Gerber, Evaluating physiological load of workers with wearable sensors, Comput. Civ. Eng. (2012) 405–412, http://dx.doi.org/10.1061/9780784412343.0051.

[62] M. Garet, G. Boudet, C. Montaurier, M. Vermorel, J. Coudert, A. Chamoux, Estimating relative physical workload using heart rate monitoring: a validation by whole-body indirect calorimetry, Eur. J. Appl. Physiol. 94 (2005) 46–53, http://dx.doi.org/10.1007/s00421-004-1228-9.

[63] R. Maiti, Workload assessment in building construction related activities in India, Appl. Ergon. 39 (2008) 754–765, http://dx.doi.org/10.1016/j.apergo.2007.11.010.

[64] U. Gatti, G. Migliaccio, Using wearable physiological status monitors for analyzing the physical strain-productivity relationship for construction tasks, Comput. Civ. Eng. (2012) 577–585 http://cedb.asce.org/cgi/WWWdisplay.cgi?294220 (accessed December 10, 2015).

[65] J.A. Boulant, Role of the preoptic-anterior hypothalamus in thermoregulation and fever, Clin. Infect. Dis. 31 (Suppl. 5) (2000) S157–S161, http://dx.doi.org/10.1086/317521.
[66] N. Charkoudian, Skin blood flow in adult human thermoregulation: how it works, when it does not, and why, Mayo Clin. Proc. 78 (2003) 603–612, http://dx.doi.org/10.4065/78.5.603.
[67] W.L. Kenney, J.M. Johnson, Control of skin blood flow during exercise, Med. Sci. Sports Exerc. 24 (1992) 303–312 http://europepmc.org/abstract/med/1549024 (accessed November 9, 2015).
[68] A.J. Young, J.W. Castellani, Exertion-induced fatigue and thermoregulation in the cold, Comp. Biochem. Physiol. A Mol. Integr. Physiol. 128 (2001) 769–776, http://dx.doi.org/10.1016/S1095-6433(01)00282-3.
[69] C. Huizenga, H. Zhang, E. Arens, D. Wang, Skin and core temperature response to partial- and whole-body heating and cooling, J. Therm. Biol. 29 (2004) 549–558, http://dx.doi.org/10.1016/j.jtherbio.2004.08.024.
[70] J.M. Johnson, Exercise in a hot environment: the skin circulation, Scand. J. Med. Sci. Sports 20 (2010) 29–39, http://dx.doi.org/10.1111/j.1600-0838.2010.01206.x.
[71] J.M. Johnson, Nonthermoregulatory control of human skin blood flow, J. Appl. Physiol. 61 (1986) 1613–1622 http://www.ncbi.nlm.nih.gov/pubmed/20036842.
[72] I.D. Swain, L.J. Grant, Methods of measuring skin blood flow, Phys. Med. Biol. 34 (1989) 151–175, http://dx.doi.org/10.1088/0031-9155/34/2/001.
[73] S.R. Tripathi, E. Miyata, P. Ben Ishai, K. Kawase, Morphology of human sweat ducts observed by optical coherence tomography and their frequency of resonance in the terahertz frequency region, Sci. Rep. 5 (2015) 9071, http://dx.doi.org/10.1038/srep09071.
[74] J.S. Petrofsky, Resting blood flow in the skin: does it exist, and what is the influence of temperature, aging, and diabetes? J. Diabetes Sci. Technol. 6 (2012) 674–685, http://dx.doi.org/10.1177/193229681200600324.
[75] Y. Chen, B. Lu, Y. Chen, X. Feng, Breathable and stretchable temperature sensors inspired by skin, Sci. Rep. 5 (2015) 11505, http://dx.doi.org/10.1038/srep11505.
[76] S. Bornmyr, H. Svensson, B. Lilja, G. Sundkvist, Skin temperature changes and changes in skin blood flow monitored with laser Doppler flowmetry and imaging: a methodological study in normal humans, Clin. Physiol. 17 (1997) 71–81, http://dx.doi.org/10.1046/j.1365-2281.1997.01313.x.
[77] A. Ghahramani, G. Castro, B. Becerik-Gerber, X. Yu, Infrared thermography of human face for monitoring thermoregulation performance and estimating personal thermal comfort, Build. Environ. 109 (2016) 1–11, http://dx.doi.org/10.1016/j.buildenv.2016.09.005.
[78] Garmin Vivofit Activity Tracker, (n.d.). https://buy.garmin.com/en-US/US/into-sports/health-fitness/previous_models_activity_tracking/vivofit-/prod143405.html (accessed July 13, 2016).
[79] Neurosky Mindwave, (n.d.). http://store.neurosky.com/pages/mindwave (accessed July 13, 2016).
[80] NeuroExperimenter Software, (n.d.). http://store.neurosky.com/products/neuroexperimenter (accessed July 13, 2016).
[81] R.S. Burnham, R.S. McKinley, D.D. Vincent, Three types of skin-surface thermometers, Am. J. Phys. Med. Rehabil. 85 (2006) 553–558, http://dx.doi.org/10.1097/01.phm.0000223232.32653.7f.
[82] T.P. Whetzel, S.J. Mathes, Arterial anatomy of the face: an analysis of vascular territories and perforating cutaneous vessels, Plast. Reconstr. Surg. 89 (1992), 591-603-605. http://www.ncbi.nlm.nih.gov/pubmed/1546070.
[83] Ben Houston, Standard Male Figure, Clara.io, 2014 https://clara.io/view/d49ee603-8e6c-4720-bd20-9e3d7b13978a/webgl.
[84] G.A. Borg, Psychophysical bases of perceived exertion, Med. Sci. Sports Exerc. 14 (1982) 377–381, http://dx.doi.org/10.1249/00005768-198205000-00012.
[85] R. Eston, M.C. Varley, G.P. Elias, R. Aughey, I. Mujika, R.G. De Txabarri, et al. Use of Ratings of Perceived Exertion in Sports2012.
[86] CDC, Perceived Exertion (Borg Rating of Perceived Exertion Scale), (n.d.). http://www.cdc.gov/physicalactivity/basics/measuring/exertion.htm (accessed November 12, 2015).
[87] M. Kay, K. Rector, S. Consolvo, B. Greenstein, J. Wobbrock, N. Watson, et al., PVT-Touch: Adapting a Reaction Time Test for Touchscreen DevicesProc. ICTs Improv. Patients Rehabil. Res. Tech., IEEE 2013, pp. 248–251, http://dx.doi.org/10.4108/icst.pervasivehealth.2013.252078.
[88] J. Dorrian, G.D. Roach, A. Fletcher, D. Dawson, Simulated train driving: fatigue, self-awareness and cognitive disengagement, Appl. Ergon. 38 (2007) 155–166, http://dx.doi.org/10.1016/j.apergo.2006.03.006.
[89] S.A. Ferguson, G.M. Paech, J. Dorrian, G.D. Roach, S.M. Jay, Performance on a simple response time task: is sleep or work more important for miners? Appl. Ergon. 42 (2011) 210–213, http://dx.doi.org/10.1016/j.apergo.2010.06.010.
[90] J. Geiger-Brown, V.E. Rogers, A.M. Trinkoff, R.L. Kane, R.B. Bausell, S.M. Scharf, Sleep, sleepiness, fatigue, and performance of 12-hour-shift nurses, Chronobiol. Int. (2012) http://www.tandfonline.com/doi/abs/10.3109/07420528.2011.645752 (accessed November 13, 2015).
[91] T.P. Krauss, L. Shure, J.N. Little, Signal Processing Toolbox for Use with Matlab, 1994.
[92] S.J. Orfanidis, Introduction to Signal Processing, Prentice Hall, 1996.
[93] G. Tanda, Skin temperature measurements by infrared thermography during running exercise, Exp. Thermal Fluid Sci. 71 (2015) 103–113, http://dx.doi.org/10.1016/j.expthermflusci.2015.10.006.
[94] A. Merla, P.A. Mattei, L. Di Donato, G.L. Romani, Thermal imaging of cutaneous temperature modifications in runners during graded exercise, Ann. Biomed. Eng. 38 (2010) 158–163, http://dx.doi.org/10.1007/s10439-009-9809-8.
[95] J. Karvonen, T. Vuorimaa, Heart rate and exercise intensity during sports activities, Sports Med. 5 (1988) 303–312, http://dx.doi.org/10.2165/00007256-198805050-00002.
[96] K. Murphy, Machine Learning: A Probabilistic Perspective, 2012 http://dx.doi.org/10.1007/SpringerReference_35834.
[97] Neurosky, What Are the Different EEG Band Frequencies?, (n.d.). http://support.neurosky.com/kb/science/eeg-band-frequencies (accessed July 13, 2016).
[98] D. Formenti, A. Merla, J.I. Priego Quesada, The Use of Infrared Thermography in the Study of Sport and Exercise Physiology, Springer International Publishing, 2017 111–136, http://dx.doi.org/10.1007/978-3-319-47410-6_5.
[99] A.J.E. Bach, I.B. Stewart, G.M. Minett, J.T. Costello, A. K, et al., Does the technique employed for skin temperature assessment alter outcomes? A systematic review, Physiol. Meas. 36 (2015) R27–R51, http://dx.doi.org/10.1088/0967-3334/36/9/R27.
[100] V. Bernard, E. Staffa, V. Mornstein, A. Bourek, Infrared camera assessment of skin surface temperature – effect of emissivity, Phytopathol. Mediterr. 29 (2013) 583–591, http://dx.doi.org/10.1016/j.ejmp.2012.09.003.
[101] N.A.S. Taylor, M.J. Tipton, G.P. Kenny, Considerations for the measurement of core, skin and mean body temperatures, J. Therm. Biol. 46 (2014) 72–101, http://dx.doi.org/10.1016/j.jtherbio.2014.10.006.
[102] M.J. Buono, A. Jechort, R. Marques, C. Smith, J. Welch, K.B.L., J.L. Bruning, et al., Comparison of infrared versus contact thermometry for measuring skin temperature during exercise in the heat, Physiol. Meas. 28 (2007) 855–859, http://dx.doi.org/10.1088/0967-3334/28/8/008.
[103] P.M. Prendergast, Anatomy of the face and neck, Cosmet. Surg, Springer Berlin Heidelberg, Berlin, Heidelberg 2013, pp. 29–45, http://dx.doi.org/10.1007/978-3-642-21837-8_2.