A New Approach to Detect the Physical Fatigue Utilizing Heart Rate Signals

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Abstract

Aim: One of the most crucial and common occupational hazards in different industries is physical fatigue. Fatigue plays a vast role in all industries in terms of health, safety, and productivity and is continually ranked among the top-five health-related risk factors year after year. The current study focuses on a novel method to detect workers’ physical fatigue employing heart rate signals. Materials and Methods: First, domain features are extracted from the heart signals utilizing different entropies and statistical tests. Then, K-nearest neighbors algorithm is used to detect the physical fatigue. The experimental results reveal that the proposed method has a good performance to recognize the physical fatigue. Results: The achieved measures of accuracy, sensitivity, and specificity rates are 78.18%, 60.96%, and 82.15%, respectively, discreetly for fatigue detection. Discussion: Based on the achieved results, it is conceived that monitoring of heart rate signals is an effective tool to assess the physical fatigue in manufacturing and construction sites since there is a direct relationship between fatigue and heart rate features. The results presented in this article showed that the proposed method would work well as an effective tool for accurate and real-time monitoring of physical fatigue and help to increase workers’ safety and minimize accidents. Conclusion: The results presented in this article shows that the proposed method would work well as an effective tool for accurate and real-time monitoring of physical fatigue and helps to increase workers’ safety and minimize accidents.

Keywords: Entropy, hear rate, physical fatigue

INTRODUCTION

Construction is one of the largest and most hazardous industrial sectors, globally. It is a priority industry for worker health and safety and has a disproportionately high rate of recorded accidents.[1] Construction had the highest work-related injury or illness in 2017–2018.[2] Each year, there are at least 60,000 fatal accidents (one of every six fatal accidents at work) on construction sites around the world. Around 25%–40% of work-related deaths occur in construction sites in industrialized countries, even though the sector employs only 6%–10% of the workforce.[3] In some countries, it is estimated that 30% of workers in this industry suffer from back pains or other musculoskeletal disorders.[2]

Fatigue plays a vast role in all industries in terms of health, safety, and productivity and is continually ranked among the top-five health-related risk factors year after year.[3,4] Fatigue in the workplace is a multidimensional construct that diminishes a worker’s performance.[5] It is estimated that fatigue costs more than $18 billion per year in lost productivity alone, of which 84% is due to the reduced performance at work.[3,4] With increasing concerns regarding occupational safety and health, managing excessive physical workloads of workers is critical to prevent workers’ fatigue, injuries, errors, or accidents at physically demanding workplaces.[3] Experience has shown that a preventative safety culture is beneficial for workers, employers, and governments alike.[8]

In previous studies, a wide range of subjective and objective methods have been used to assess the workers’ fatigue. The
subjective methods used in the previous studies include interviews, questionnaires, Swedish Occupational Fatigue Inventory, and psychomotor vigilance test. However, the results of these methods usually suffer from subjective bias and intrusiveness to a worker’s tasks. Wearable sensors enable the continuous monitoring of vital signals which can provide early warning systems for workers with high-risk health issues. Wearable sensors are currently being used to manage fatigue in professional athletics, transportation, and mining industries. However, wearable sensor application for fatigue assessment in the industry is on its first steps.

The previous studies harnessed the physiological signals to estimate the fatigue level since it is resulted from physical overexertion and is associated with physiological symptoms. Chang et al. used heart rate to compare emotional stress and physiological strain for different occupations. They investigated the effect of occupation on fatigue and physical symptoms that high-elevation construction workers experience. Venugopal et al. used multiple time window features to recognize fatigue from surface electromyography signals. She, et al. designed a monitoring and estimation system for the degree of fatigue using heart rate and body movement data. Maman et al. estimated physical fatigue using body move acceleration and heart rate data. Aryal et al. conducted a simulated construction task for monitoring physical fatigue by measuring changes in heart rate, skin temperature, and brain signals. Surangsrirat et al. studied the effect of fatigue on heart rate, body temperature, and skin humidity of people working in high-temperature environment. Zhang et al. used jerk, the time derivative of acceleration, to assess fatigue in physically demanding tasks.

Objective

Based on the conducted literature review, heart rate is the most widely used physiological symptom for monitoring and detecting a worker’s fatigue. Monitoring of heart rate signals is an effective tool to assess the physiological strain of subjects in manufacturing and construction sites. It has been proved that there is a direct relationship between physical fatigue and heart rate metrics such as heart rate, heart rate variability, and percentage of heart rate reserve according to the previous studies.

This article proposes a new approach for detecting physical fatigue using heart rate signal monitoring which fills the gap in the literature. In the proposed method, the patterns of physiological signals are studied for fatigue detection. Different entropies and statistical tests are used to extract features.

Using the proposed method, physical fatigue is detected real time using heart signals. Moreover, physical fatigue is predicted more accurately. The proposed method provides an efficient tool to enhance the workers’ health and safety in real manufacturing and construction sites and prevent accidents.

Materials and Methods

In this section, the method used for data collection is first introduced. The physically fatiguing task, different methods for entropy calculation, different methods of statistical tests, and classification method are introduced afterward.

Data collection (participants)

The physiological data collected by Sedighi Maman et al. were used to detect the workers’ physical fatigue. Their protocol consisted of three physically demanding tasks. Five males and three females from the local community were engaged for a duration of 3.5 months in their research. The age range of the participants was between 18 and 62 years. Two of eight participants were from manufacturing industries and the rest were students exposed to different physical activities.

Physically fatiguing task

In Sedighi Maman et al’s study, participants underwent one experimental session. In this session, one physically fatiguing task should be performed within 3 h. The task was divided into 1-h periods. The physical fatiguing task was named as manual material handling (MMH). The MMH task included selection of the packages with different weights, namely 26 kg, 18 kg, or 10 kg, and transferring them to a two-wheeled trolley and moving it to another section and stacking them at the certain locations. The palletization of the package was done in accordance with the packing orders received. One min was the median time for moving one package in one cycle. During 3-h period, each scenario consisted of moving 18 packages summing up to a total of 108 packages as a whole.

Method

Using statistical tests and fractal dimensions (FDs), some features were extracted in the proposed method. By applying k-nearest neighbors (KNNs) algorithm, we tried to do classification. The best value of $K$ was also selected
by changing this parameter from 1 to 40. According to the accuracy of results, when $K$ was 15, we could achieve the best performance. KNN is used because of its classification speed. Actually, there is no learning time. KNN is a lazy learner as it does not learn a classification function from the training data. It remembers the training dataset and uses them for classification.

**Nonlinear features based on fractal dimensions**

In addition, to mean, standard deviation, minimum, and maximum, some other features such as Higuchi FD (HFD) and Katz FD were also used.

**Higuchi fractal dimension**

Higuchi introduced the FD calculation of a curve in a plane in 1988.\[sup\]28\[sub\] It is nonlinear measure in the time domain for waveform complexity. Time sequences $x(1), x(2), ..., x(N)$ can be utilized as signals or discretized functions.\[sup\]29\[sub\] A self-similar new time series $X_n^m$ can be measured from the starting time sequence as:

$$X_n^m: X(m), x(m+k), x(m+2k), ..., x(m+\text{int} [(N-k)/k] k)$$  \hspace{1cm} (1)

Where $k$ is the time interval, $m = 1, 2, ..., k$ where $m$ is the initial time, $k = 1, ..., k_{\text{max}}$, $\text{int}(r)$ is the integer part of the real number $r$; $k_{\text{max}}$ is a free parameter. The curves $X_n^m$ or each of the k time series determines the length of the curve $L_m(k)$.

$$L_m(k) = \frac{1}{k} \left[ \sum_{i=1}^{\text{int}(N-k/k)} |x(m + ik) - x(m + (i-1)k)| \right]$$

$$+ \left[ \frac{N-1}{\text{int}(N-m) \cdot \text{int}(N-k/k)} \right]$$  \hspace{1cm} (2)

Where $(N-1)/(\text{int} [(N-m)/k] k)$ is a normalization factor and $N$ is the length of the original time series. The mean value of $L(k)$ was averaged for all m results in $L_m(k)$ for $k = 1, ..., k_{\text{max}}$ as expressed below:

$$L(k) = \frac{\sum_{m=1}^{k} L_m(k)}{k}$$  \hspace{1cm} (3)

HFD was calculated as the slope of least square linear best fit and an array of mean values is termed as $L(k)$. Hence, HFD is termed as:

$$\text{HFD} = \log_{10}(L\left[k\right]) / \log_{10}(1/k)$$  \hspace{1cm} (4)

Windows are the original signal or curve divided into smaller parts with or without overlapping in real scenario. Hence, with or without overlap, HFD values can be estimated.

**Katz fractal dimension**

The calculation of FD was devised by Katz in 1988.\[sup\]30\[sub\] It is a measure of the ratio of curve length $L$, which is summed up by the Euclidean distances between two consecutive points compared to the maximum distance $d$ from the first point to any point in the frame.\[sup\]31\[sub\] It can be termed as the ratio of the length of the curve divided by the line having maximum Euclidean distance from the initial point. The FD is defined as:

$$FD = \frac{\log_{10}(L)}{\log_{10}(d)}$$  \hspace{1cm} (5)

Where $L$ is the summation of the Euclidean distances between consecutive points or the total longitude of the curve.

$$L = \sum_{i=1}^{N} \text{dist}(s_i, s_{i+1}), i = 1, ..., N-1$$  \hspace{1cm} (6)

Where $d$ is the planar extension of the curve, which is the distance between the furthest point and the first point in the sequence. $D$ can be termed as:

$$d = \text{Max}(\text{dist}[s_i, s_j], i = 1, ..., N)$$  \hspace{1cm} (7)

Katz suggested the mean distance between the consecutive points, hence normalizing $L$ and $d$. Here $a = L/N$, where $N$ is the step numbers in the curve. The equation (5) becomes:

$$FD = \frac{\log_{10}(L)}{\log_{10}(d)} = \frac{\log_{10}(L)}{\log_{10}(d) + \log_{10}(N)}$$  \hspace{1cm} (8)

**K-nearest neighbors**

The KNN algorithm is a simple, supervised machine-learning classifier that can be used to solve both regression and classification problems. One of the advantages of this algorithm is that it is easy to implement and understand. KNN supposes that similar things exist in close proximity. In other words, similar things are near to each other. KNN categorizes the unknown labels based on similarity measures.

**Results**

KNN algorithms employed to obtain the accuracy of fatigue detection in MMH task in the present study. The accuracy, sensitivity, and specificity of algorithms were used for their performance comparison.\[sup\]32\[sub\]-\[sup\]37\[sub\] The implementation of these algorithms is represented in Table 1. As shown in Table 1, the accuracy of algorithms will be increased as the value of $K$ is enhanced (goes up). In addition, the value of specificity is higher than the values of sensitivity in KNN algorithms.

| Performance (%) of k-nearest neighbors with different Ks |
|-----------------------------------------------|
| Performance \ algorithm name | Accuracy | Sensitivity | Specificity | AUC |
| KNN (K=1) | 57.99±5.11 | 44.14 | 60.56 | 0.791 |
| KNN (K=3) | 60.82±3.06 | 46.09 | 64.44 | 0.721 |
| KNN (K=5) | 65.50±4.16 | 52.92 | 69.44 | 0.702 |
| KNN (K=7) | 71.21±4.59 | 54.74 | 75.93 | 0.695 |
| KNN (K=9) | 74.96±3.95 | 55.22 | 79.59 | 0.698 |
| KNN (K=11) | 75.29±4.39 | 57.48 | 77.96 | 0.693 |
| KNN (K=13) | 76.49±4.27 | 59.82 | 80.30 | 0.693 |
| KNN (K=15) | 78.18±4.68 | 60.96 | 82.15 | 0.68 |

KNN: K-nearest neighbors, AUC: Area under the curve
It is worth to note that the value of AUC will be decreased when the accuracy of algorithm is increased by increasing the values of K.

To draw a meaningful comparison between different KNNs in various conditions, the receiver operating characteristic (ROC) curve of algorithms is shown [Figure 2].

**DISCUSSION**

Data source used in the present study was collected earlier by Sedighi Maman et al.[27] to detect workers’ physical fatigue. They employed five different sensors’ features in their study. As a contrast, this research has only dealt with the data extracted from the heart rate sensor. Although the focus of Sedighi Maman et al.[27] research was on using statistical tests, in the current study, some important features were extracted from heart signals using entropies and statistical tests to detect the workers’ physical fatigue. KNN algorithms were used for classification. To see the impact of different values of K on the output of algorithms, the value of K started to increase from one. It was concluded that the accuracy of algorithm is increased as the value of K is enhanced. Based on the achieved results, it is conceived that monitoring of heart rate signals is an effective tool to assess physical fatigue in manufacturing and construction sites since there is a direct relationship between fatigue and heart rate features. The results presented in this article showed that the proposed method would work well as an effective tool for accurate and real-time monitoring of physical fatigue and help to increase workers’ safety and minimize accidents.

**CONCLUSION**

The proposed method can be a practical tool to develop warning systems against high levels of physical fatigue and give an increased amount of rest between tasks to improve workers’ safety. Collecting more data sources can be led to more accurate results. As features play an important role in the implementation of algorithm, extracting new features employing other entropies may help to improve the accuracy of the proposed method. It can be concluded that deep-learning algorithms make more meaningful and valuable contributions to the research in this area.

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**Conflicts of interest**

There are no conflicts of interest.

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