"PREDICTION OF FATIGUE LEVEL DURING EXERCISE IN VIRTUAL REALITY ENVIRONMENT FOR HAJJ PILGRIMAGE".

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ABSTRACT

Strenuous activities, especially through the eight days of the Hajj pilgrimage journey, may cause exhaustion for the Hajj pilgrims after completing each stage. Environmental factors such as being in overcrowded places and having to endure hot temperatures alongside continuous vigorous activities during the Hajj can result in serious exhaustion where individual body muscles and the cardio-respiratory systems are affected, resulting in muscle cramps, dehydration and possibly illness such as fever, hypertension, stroke, asthma and heart attack. This paper aims to introduce a wearable device that can assist the pilgrims to monitor their exhaustion threshold. To test this, 30 healthy people who are about to perform hajj were chosen as respondents for the study. These subjects performed fatigue-induced exercises by walking or running on a treadmill which is integrated with a 3D virtual reality environment of Makkah. The speed of the treadmill increased its intensity at every 2 minute interval from 4 km per hour to 12km per hour until the subjects' exhaustion threshold is reached. Simultaneously, heart rate, blood pressure and muscle fatigue were closely monitored using the developed device attached to their wrists. This device uses an electrocardiogram (ECG) and an electromyography (EMG) measurement and produces three different colour signals ranging from green, yellow and red to indicate the subjects' exhaustion level. The data collection of each subject was then analysed using the SPSS software and also modelled in MATLAB software for the ANN method. As a result, the accuracy of prediction model presented from this study is 89.3%, indicating a high indicator for the fatigue level. Overall, this study is expected to be beneficial for hajj pilgrims who wish to evaluate their own body fitness when preparing for their Hajj pilgrimage.

Keywords: hajj pilgrims, virtual reality, monitoring device, exhaustion threshold, fatigue.

Introduction

The Hajj pilgrimage is a mass gathering performed by Muslims in Makkah. It involves a lot of physical activities such as the *wukuf*, *tawaf* and *sa'ie* to complete each step of the pilgrimage. Most of these activities are categorized as a form of aerobic exercise as it consumes oxygen without producing lactic acid. Pilgrims with low muscle strength and endurance are still able to perform the hajj even when they are not physically fit. However, muscle fatigue during the pilgrimage is likely to occur for these types of pilgrims. Muscle fatigue is the decline of muscle contraction when producing force during movement.

On the other hand, physical fatigue refers to muscle fatigue which can be monitored from the muscle activity when performing any physical activity or exercise. One of the several methods to measure the electrical activity of the musculoskeletal system during exercise is through the use of the electromyograph (EMG). EMG measures the electrical activity of muscle fibre during the contraction phase. It also measures the muscle response by a nerve stimulation from the nervous system (Elamvazuthi et al., 2015). The EMG uses two techniques which are the invasive or non-invasive method, depending on the type of electrodes used for the measurement. The most common method used by previous researchers due to being much easier, faster and has less severity on the body is the non-invasive method with surface electrodes. This is widely used in clinical fields (Hawkes et al., 2015), rehabilitation (Elamvazuthi et al., 2015), ergonomics (Jia & Nussbaum, 2016) and sports applications (Ahmad, Najeb, & Soeed, 2019).

Interestingly, the use of EMG to measure muscle fatigue is still rare for hajj pilgrimage activities. In recent years, there has been an increasing pool of literature on fatigue detection using EMG monitoring with signal processing analysis (Ahmad, Jamaludin, Aishah, & Jamaludin, 2019; Asefi, Moghimi, Kalani, & Moghimi, 2016). Moreover, there are several existing methods which can be employed to process raw EMG data such as wavelet analysis, time-frequency approach, auto-regressive model and artificial intelligence (Ahmad, Jamaludin, & Omar, 2018; Jamaluddin et al., 2015; Shair, Ahmad, Marhaban, Mohd Tamrin, & Abdullah, 2017).

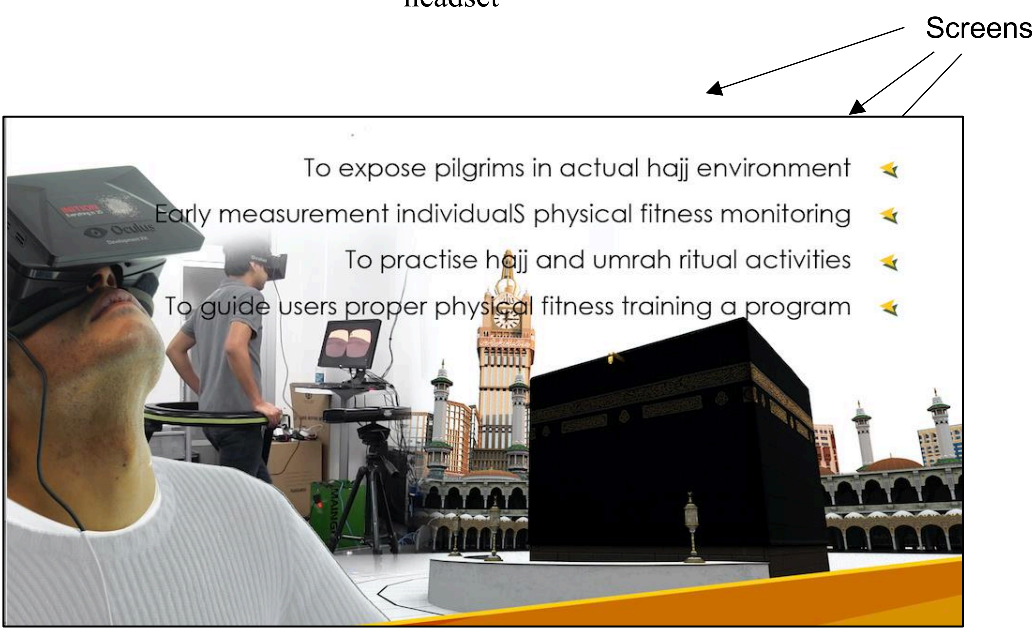
Virtual reality (VR) is an interactive environment created using computer software as the current learning approach. The design of VR can be customized depending on its use to explore simulated environments. In addition, immersive VR could provide new experiences for the user to interact and communicate when entering this environment. Therefore, a Hajj environment in VR could help the user to physically perform the Hajj ritual and evaluate their level of fitness before going to Makkah to perform the real pilgrimage journey.

The purposes of this study then is to investigate the effect of performing exercise while in a 3D Hajj virtual reality (VR) environment and to predict fatigue level using the machine learning method based on EMG signals collected from the experiment.

Methodology

Thirty healthy subjects were selected randomly (Age: 24.97$\pm$4.25 years old and BMI: 23.08$\pm$4.78) but also complying with the inclusion criteria established earlier. An experiment was setup as illustrated in Figure 1, where the subject is asked to perform an exercise in the immersive virtual reality displaying a 3D hajj environment. By integrating the use of a treadmill, the Oculus VR headset as well as the VR environment, the subject is put into a simulation of the hajj pilgrimage. At the same time, a CAVE showcase was also set-up to simulate another 3D Hajj VR environment, as shown in Figure 1b. In this set-up, three screens around the CAVE showcase is incorporated with the surrounding sound system of a Hajj VR environment.

Figure 1a: The immersive virtual reality set-up using the Oculus VR headset



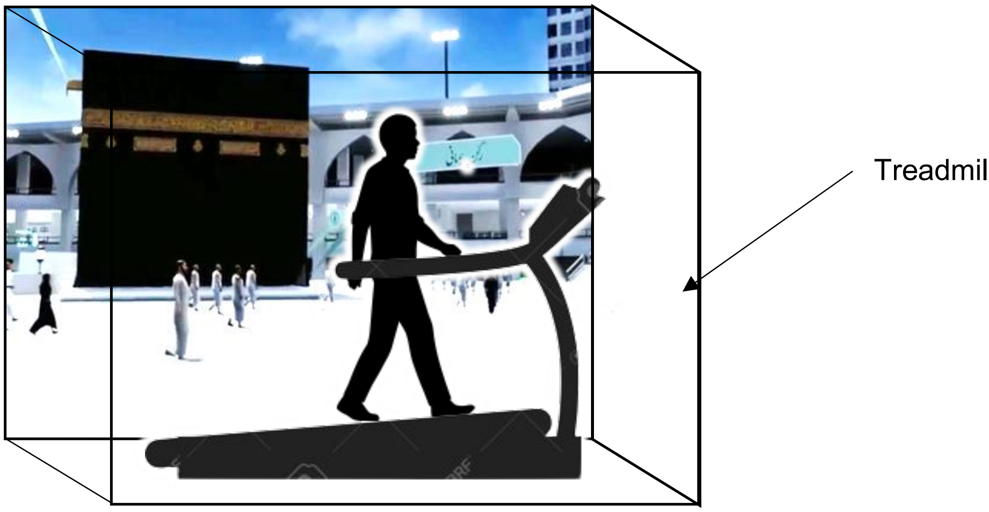
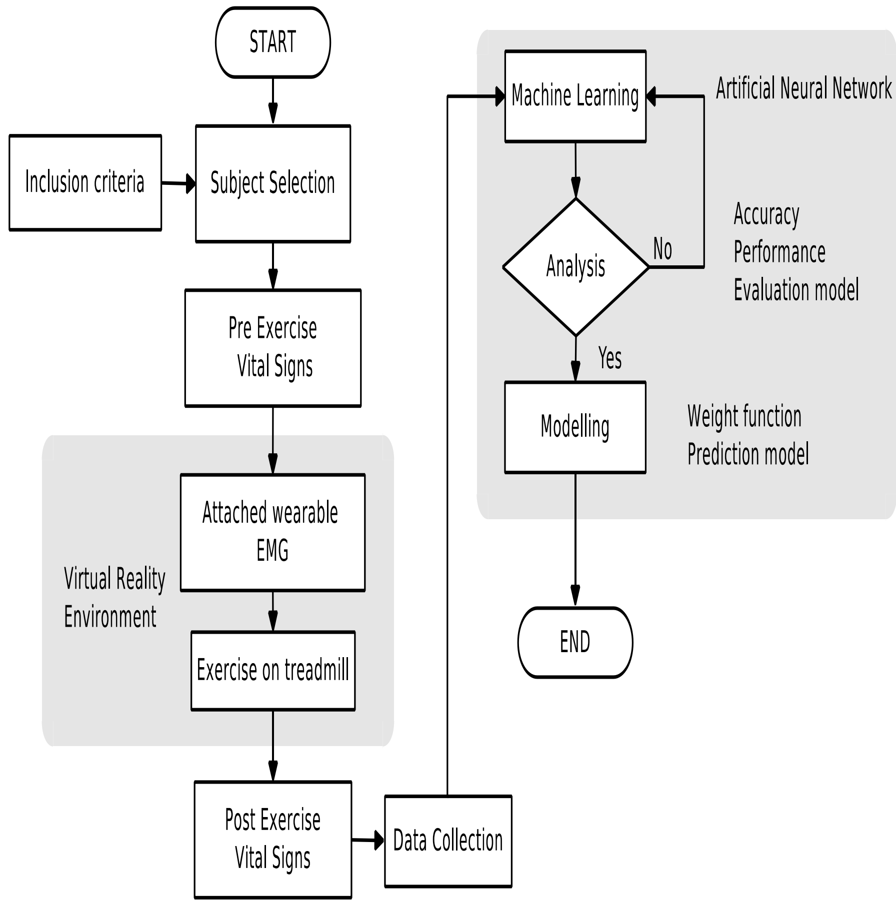


Figure 1b: The immersive virtual reality set-up using CAVE showcase

Before the start of the experiment, measurements of vital signs such as blood pressure and heart rate of the subjects were recorded. A wearable device using an electrocardiogram (ECG) and an EMG was then attached to the body to measure muscle activity of the subjects' lower limbs once the experiment starts. The subject was then instructed to walk on the treadmill for five minutes before their vital signs were measured again using the EMG device. This device produced three different colour signals ranging from green, yellow and red to indicate the subjects' exhaustion level. To reach that exhaustion level, the speed of the treadmill increased its intensity at every 2 minute interval from 4km perhour to 12km per hour until subjects' exhaustion threshold was reached. During the experiment, all measurements were obtained in real-time and transmitted to the computer wirelessly.

Next, data collection from computer was then analysed and used to develop a prediction model using an artificial neural network. Finally, that model can be used to predict muscle fatigue for the other samples.

Figure 2: Research Flowchart



All these steps have been simplified into research flowchart as shown in Figure 2 above. Two types of software were used to produce the results which were SPSS for statistical analysis and MATLAB for signal processing respectively. Moreover, the modelling in machine learning was by creating the weight function from training and validation procedure. High accuracy was selected as the best model to perform its function.

Results

Table 1 indicates the data collection of vital signs parameter for blood pressure (systolic and diastolic) and heart rate for pre- and post-exercise. Standard deviation was observed as the increment value between pre- and post-exercise for all three parameters. Hence, this is evidence of selected parameter that was affected by exercise, similar to the findings by Ahmad et al. (2019). However, the error mean for heart rate is little bit higher compared to the others, and this poses as unstable data in the database.

Parameters	Mean	Std. Deviation	Std. Error Mean
PreSys	118.67	8.774	1.602
PreDias	75.40	5.096	0.930
PostSys	123.10	9.305	1.699
PostDias	78.57	5.328	0.973
PreHR	81.67	12.021	2.195
PostHR	91.93	15.713	2.869

Table 1: Vital signs parameter

In order to check the data, a boxplot was illustrated in Figure 3. It was found that there were some outliers that distrupted the data which is outside the accepted range. Therefore, that outlier needed to be removed from the analysis in order to minimize the error. Moreover, it also shows that the increment of systolic blood pressure is from 118.67mmHg to 123.10mmHg.

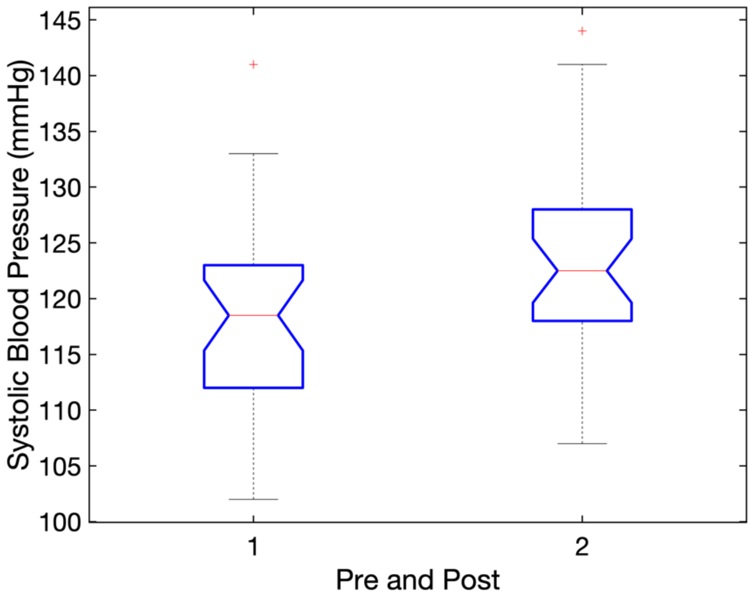


Figure 3: Boxplot for Blood Pressure during pre- and post-exercise.

Interestingly, the details of sampling can be observed from Bland-Altman plot in Figure 4. It shows the upper and lower range of accepted 95% confidence interval represented by 1.96σ. The upper and lower limit is at 141.16mmHg and 105.13mmHg respectively. Again, it was revealed that the outlier is at sample number 30.

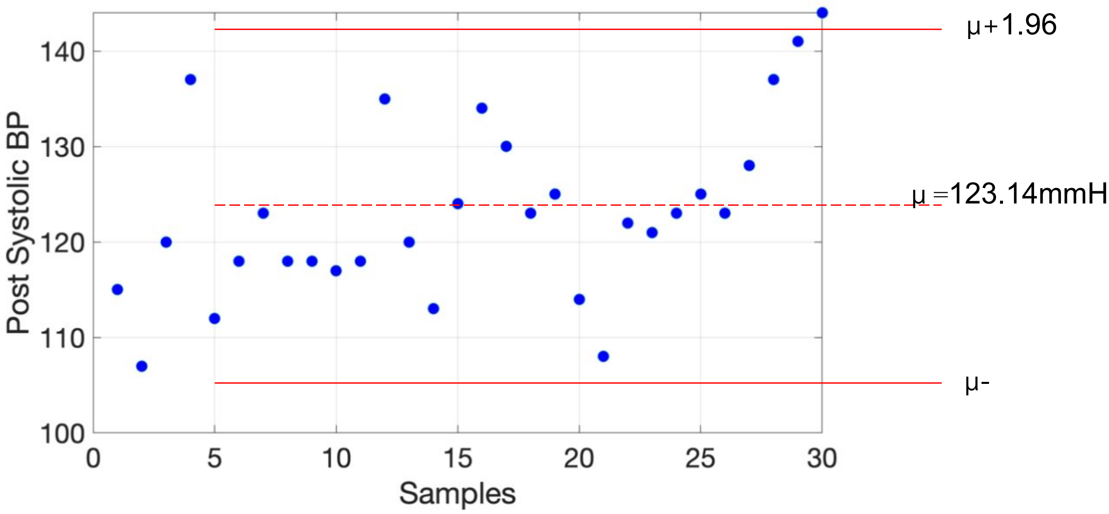


Figure 4: Bland-Altman plot

The bivariate correlation by Pearson demonstrates the relationship between pre- and post-exercise parameter as shown in Table 2. Obviously, there is no significant difference between blood pressure and heart rate for both systolic and diastolic. It gives the lowest correlation factor by -0.003 and $p>0.05$. In contrast, the significant parameter was granted to the heart rate that was as high as 0.818 and $p<0.01$ level, followed by systolic and diastolic blood pressure at 0.761 and 0.473 respectively. In addition, by comparing systolic and diastolic blood pressure, it generates a pretty good value as much as 0.672 for pre-exercise and 0.679 for post-exercise while the significant is $p<0.01$.

		PreSys	PreDias	PostSys	PostDias	PreHR	PostHR
PreSys	Pearson Correlation	1	0.672**	0.761**	0.597**	-0.003	0.056
PreDias	Pearson Correlation	0.672**	1	0.424*	0.473**	0.122	0.179
PostSys	Pearson Correlation	0.761**	0.424*	1	0.679**	-0.132	-0.014
PostDias	Pearson Correlation	0.597**	0.473**	0.679**	1	-0.084	-0.122
PreHR	Pearson Correlation	-0.003	0.122	-0.132	-0.084	1	0.818**
PostHR	Pearson Correlation	0.056	0.179	-0.014	-0.122	0.818**	1

Table 2: Correlations

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

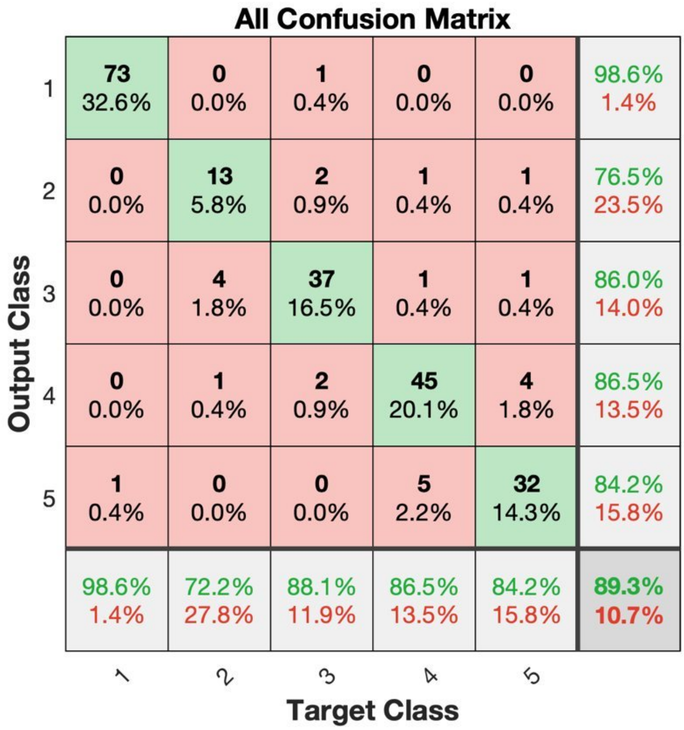
Through linear regression, this model produced coefficient correlation R = 0.663, which is considered as moderate relationship in a scatter plot. The dependent variable of this coefficient is presented by the level of fatigue. Therefore, column B in the Table 3 is coefficient for each parameter to predict the fatigue level.

Model		Unstandardized Coefficients	
		B	Std. Error
1	(Constant)	6.938	5.878
	PreSys	0.072	0.062
	PreDias	0.055	0.078
	PostSys	-0.161	0.056
	PostDias	0.086	0.090
	PreHR	0.020	0.050
	PostHR	-0.056	0.037

Table 3: Coefficients

Lastly, the confusion matrix in Figure 5 provides a better prediction model with the high accuracy of 89.3%. This is higher than the method used in linear regression. This is due to machine learning via artificial neural network that was trained by feature extraction and generated more samples from the signals obtained. The total input for this method is 134 and correctly predicts the level of fatigue as denoted in the green boxes. Moreover, the prediction fatigue level is more than 80% while for level 2 it is vice versa.

Figure 5: Confusion matrix for model development



Conclusion

This study was conducted for two purposes - to investigate the effect of exercise in virtual reality, and to predict fatigue level using machine learning method. All objectives were achieved and the findings are promising for prediction with accuracy being 89.3% correct. As a result, this method can be applied to a different application related to physical fatigue by strenuous activities. In other words, the method can be beneficial to hajj pilgrims who wish to evaluate their own body fitness when preparing for their Hajj pilgrimage.

References

Ahmad, Z., Jamaludin, M. N., & Omar, A. H. (2018). Development of Wearable Electromyogram for the Physical Fatigue Detection During Aerobic Activity. *Movement, Health & Exercise*, *7*(1), 15–25. https://doi.org/http://dx.doi.org/10.15282/mohe.v7i1.225

Ahmad, Z., Jamaludin, U. K., Aishah, A. F. Q. A., & Jamaludin, M. N. (2019). Development of wearable electromyogram (EMG) device for upper extremity in aerobic exercise. *IOP Conference Series: Materials Science and Engineering*, *469*(1), 1–9.

https://doi.org/10.1088/1757-899X/469/1/012085
Ahmad, Z., Najeb, M., & Soeed, K. (2019). An effect of physical exercise-induced fatigue on the vital sign parameters : A preliminary study. *Malaysian Journal of Fundamental and Applied Sciences*, *15*(2), 173–177.
Al-Mulla, M. R., & Sepulveda, F. (2010). Novel feature modelling the prediction and detection of sEMG muscle fatigue towards an automated wearable system. *Sensors*, *10*(5), 4838–4854. https://doi.org/10.3390/s100504838
Asefi, M., Moghimi, S., Kalani, H., & Moghimi, A. (2016). Dynamic modeling of SEMG-force relation in the presence of muscle fatigue during isometric contractions. *Biomedical Signal Processing and Control*, *28*, 41–49. https://doi.org/10.1016/j.bspc.2016.04.002
Chang, K. M., Liu, S. H., & Wu, X. H. (2012). A wireless EMG recording system and its application to muscle fatigue detection. *Sensors*, *12*(1), 489–499. https://doi.org/10.3390/s120100489
Cortes, N., Onate, J., & Morrison, S. (2014). Differential effects of fatigue on movement variability. *Gait and Posture*, *39*(3), 888–893. https://doi.org/10.1016/j.gaitpost.2013.11.020
Elamvazuthi, I., Zulkifli, Z., Ali, Z., Khan, M. K. A. A., Parasuraman, S., Balaji, M., & Chandrasekaran, M. (2015). Development of Electromyography Signal Signature for Forearm Muscle. *Procedia Computer Science*, *76*, 229–234. https://doi.org/10.1016/j.procs.2015.12.347
Gart, M. S., & Wiedrich, T. A. (2017). Therapy and Rehabilitation for Upper Extremity Injuries in Athletes. *Hand Clinics*, *33*(1), 207–220. https://doi.org/10.1016/j.hcl.2016.08.016
Hawkes, D. H., Alizadehkhaiyat, O., Kemp, G. J., Fisher, A. C., Roebuck, M. M., & Frostick, S. P. (2015). Electromyographic assessment of muscle fatigue in massive rotator cuff tear. *Journal of Electromyography and Kinesiology*, *25*(1), 93–99. https://doi.org/10.1016/j.jelekin.2014.09.010
Jamaluddin, F. ., Siti A.Ahmad, Samsul Bahari Mohd Noor, Hassan, W. Z. W., Yaakob, A., Adam, Y., & Ali, S. H. . (2015). Amplitude and Frequency Changes in Surface EMG of Biceps Femoris during Five Days Bruce Protocol Treadmill Test. In *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 6219–6222).
Jia, B., & Nussbaum, M. A. (2016). Development and evaluation of an EMG-based model to estimate lumbosacral loads during seated work. *International Journal of Industrial Ergonomics*, *55*, 96–102.

https://doi.org/10.1016/j.ergon.2016.08.007

Neves, E. B., Cunha, R. M., Rosa, C., Antunes, N. S., Felisberto, I. M. V., Vilaça-Alves, J., & Reis, V. M. (2016). Correlation between skin temperature and heart rate during exercise and recovery, and the influence of body position in these variables in untrained women. *Infrared Physics and Technology*, *75*, 70–76. https://doi.org/10.1016/j.infrared.2015.12.018

Shair, E. F., Ahmad, S. A., Marhaban, M. H., Mohd Tamrin, S. B., & Abdullah, A. R. (2017). EMG Processing Based Measures of Fatigue Assessment during Manual Lifting. *BioMed Research International*, *2017*, 1–12. https://doi.org/10.1155/2017/3937254