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Modeling the Multi-Dimensional Phenomenon of Fatiguing by Assessing the Perceived Whole Body Fatigue and Local Muscle Fatigue During Squat Lifting

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무릎들기 작업 시 전신피로 감지 수준과 근육 피로도를 활용한 다면적 피로현상 모델링

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Whole body fatigue detection is an important phenomenon and the factors contributing to whole body fatigue can be controlled if a mathematical model is available for its assessment. This research study aims at developing a model that categorizes whole body exertion into fatigued and non-fatigued states based on physiological and perceived variables. For this purpose, logistic regression was used to categorize the fatigued and non-fatigued subject as dichotomous variable. Normalized mean power frequency of eight muscles from 25 subjects was taken as physiological variable along with the heart rate while Borg scale ratings were taken as perceived variables. The logit function was used to develop the logistic regression model. The coefficients of all the variables were found and significance level was checked. The detection accuracy of the model for fatigued and non-fatigues subjects was 83% and 95% respectively. It was observed that the mean power frequency of anterior deltoid and the Borg scale ratings of upper and lower extremities were significant in predicting the whole body fatigued when evaluated dichotomously ($p < 0.05$). The findings can help in better understanding of the importance of combined physiological and perceived exertion in designing the rest breaks for workers involved in squat lifting tasks in industrial as well as health sectors.

Keywords : Electromyography, Logistic Regression, Whole Body Fatigue, Fatigue Modeling, Musculoskeletal Disorders

1. Introduction

Modeling of physical fatigue has been a challenging phenomenon as there are numerous factors that contribute to it. Due to the multidimensional nature of the fatigue, different factors are incorporated for its assessment [32]. The factors may include psychological, environmental or socioeconomic [36]. In regard to the different industrial setting concerning the occupational health, scheduled rest breaks play an important role in fatigue management. Fatigue may also have indirect implications such as falls or limited visual fields which also contribute to most frequent type of injuries in construction industry [22, 23]. Physical fatigue is an accumulating phenomenon involving repetitive tasks [31], therefore wrong assessment of fatigue may lead to work related musculoskeletal disorders (WMSD). WMSD's have been

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classified as the most prevalent occupational medical condition by the European Risk Observatory report [27]. Recent trends in wearable sensors have made it possible to collect real time data thus making it possible to detect muscle fatigue [28]. Among different tasks being performed in industry squat lifting in a demanding task that involved both upper and lower body exertion. Over exertion in such case causes loss of working hours to the industry in the form of errors and accidents.

Fatigue is a gradual phenomenon and the precursors of fatigue sometimes get un-noticed. As the change in magnitude of the precursors is small at the early onset of fatigue, therefore it is not a good practice to rely on only one type of variable to be chosen for fatigue detection [9].

However with proper quantification of such variables certain interventions can be made for the onset of fatigue [8]. The variables selected for fatigue quantification may infer to a single muscle or the body as a whole [1]. Therefore careful selection of variables used in quantification of fatigue is important for the type of fatigue to be detected [30]. Industrial settings involving squat lifting often design the rest brakes based on whole body fatigue therefore it is important to take the variables that contribute to whole body fatigue. Borg [6, 7] constructed a scale ranging from 0-10 to address the issue of whole body fatigue. Main aim was to correlate any physiological variable to a scale. He used heart rate as basis to construct the scale. Similarly oxygen uptake is also marked as assessment methods and has been used to assess athletes' performance [4]. Among all the techniques used to acquire physiological data, wearable sensors, such as heart rate sensor and remote EMG modules have made it easier for on field assessment of fatigue.

EMG signals are mainly used in the domains of muscle force, muscle geometry and the fatigue assessments. For the reliable assessment of fatigue accurate measurements are very important. Electromyography (EMG) has long been used to assess fatigue level by researchers for manual lifting. Among the noninvasive methods, surface electromyography (sEMG) has been used widely to quantify muscle fatigue [2, 3]. However, due to non-stationarity of the EMG signals, the frequency domain indexes of EMG have been preferred over the time-indexes to detect the muscle fatigue. Among such index is the Mean power frequency (MNF) of the EMG signal [15]. Studies has shown that the MNF can be used to detect the muscle fatigue in dynamic muscle contraction [10]. The decrease in Mean power frequency of the sEMG signal signifies the onset of the muscle fatigue and has been used in various clinical settings [17]. Squat lifting is one of the task involving the dynamic contraction of muscles of upper and lower extremity. Spectral changes in EMG signals have helped researchers gain insight of the muscles involved [35]. Thus combined EMG signals from major muscles involved in a task can help predict or classify the fatiguing process.

Classification of fatigue while combing the physiological and perceived exertion has scarcely been studied. One way to study the combined effect of different variables on an output is the Logistic regression [20]. Among the multivariate methods, Logistic regression is widely used in healthcare sciences [34]. It has been used in classifying fatigued and non-fatigued local muscle fatigue state, using EMG as well as EEG in detecting game addicted subjects [12, 37]. Unlike linear regression which uses least square error to minimize the error, the logistic regression uses maximum likelihood. With the advent of new technologies, it is able to get large data set thus making learning algorithms able to make better decisions. Attempts have been made to translate these technologies to be used in fatigue detection systems [16, 28]. However these studies used motion sensors and heart rate to evaluate the whole body fatigue. The contribution of different body extremities in dynamic lifting task can help better assessment of whole body fatigue. This can be done by studying the combined effect of physiological indicators as well as the psychological variable and then evaluating the effect of each variable.

In the light of above discussion, this study aims to develop a learning algorithm based on logistic regression that harnesses the power of sEMG large data set combines with perceived exertion of lower and upper extremity of the body and detect the whole body fatigue based on contribution of all the variables involved. The dynamic squat lifting task was used to recruit major muscles of lower and upper extremity. The data has been taken from our previously previous study [1]. The second part of the study was included in which the subjects lifted 8 kg weight for 24 sets of squats.

2. Material and Methods

2.1 Samples

For this study 25 male subjects between the ages of 28~32 were recruited from the student population with no history of low back pain [13]. This study was approved by Hanyang University Institutional Review board (IRB) bio ethics committee, South Korea. Each subject signed an informed an informed consent before the start of experimental trials. All the trials were randomized to avoid biasness.

2.2 Muscle Selection and Location of Electrodes

Surface electrodes (Ag-Ag/Cl) were used with bipolar configuration with an inter electrode distance of 20mm. EMG signals recorded from eight muscles which include divided into the upper extremity and the lower extremity. The muscles for the lower extremity included Bicep femoris (BF), rectus Femoris (RF), Vastus lateralis (VL) and gastrocnemius medialis (GS), while for the lower extremity they included anterior deltoid (AD), upper trapezius (UT), supraspinatus (SP) and medial deltoid (MD) [13, 28]. SENIAM recommendations were used for the placement and location of electrodes [21, 29]. For the bicep femoris, the electrode was placed at 50% on the line of the ischial tuberosity and the lateral epicondyle of the tibia. For the anterior deltoid, the electrodes were placed at one finger width away and anterior to the acromion. For the medial deltoid, the electrodes were placed 3 cm below the acromion, over the muscle bulk, aligned with the muscle fibers [26]. For the vastus lateralis, electrodes were placed at 2/3 on the line from the anterior spina iliaca superior to the lateral side of the patella. For the rectus femoris, the electrodes were placed at 50% on the line from the anterior spina iliaca superior to the superior part of the patella. For the gastrocnemius medialis, the subjects laid supine. The knee was extended and the foot flexed. Electrode was placed on the most prominent bulge of the muscle. For upper trapezius the electrodes were placed at 50% on the line from the acromion to the spine on vertebra C7. The supraspinatus electrodes were placed over the suprascapular fossa [26]. Maximum voluntary contraction for each muscle was attainted for the normalization of EMG signal for each muscle.

2.3 Data Acquisition and Processing

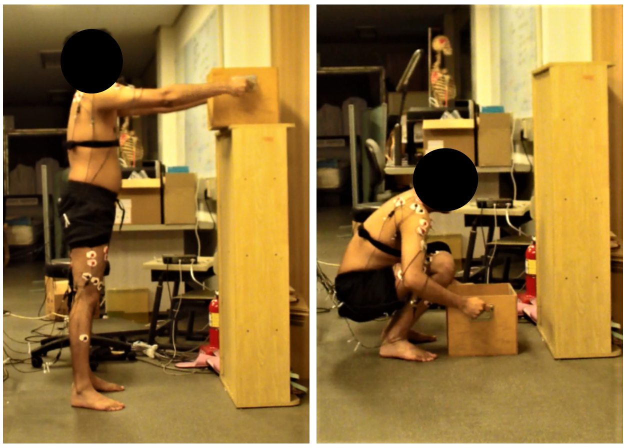
For the acquisition of EMG signals, an eight channel ME 6,000 Bittium Bio signals Ltd EMG system was used while for the heart rate, Polar heart rate censor was used [24]. The sampling frequency was set to 1,024 Hz. Movement artifacts and the noise was filtered by using band pass filter 10~500 Hz for the EMG signals. For muscle activation, Root Mean Square (RMS) value was used to find the onset and off set of the muscles [1]. The Normalized Mean Power Frequency (NMPF) of all the muscles at each was obtained for all the squat sets.

3. Experiment Design

A uniformly distributed 8kg box was used as lifting weight. The box had handle on each side. For this study, the perceived whole body fatigue was taken as the dependent variable which was categorized into fatigue and non-fatigued conditions for the sigmoid function. The slopes of the normalized EMG, heart rate and the perceived exertions from the two regions were taken as the independent variable to model the transition to fatigue was taken as independent variables.

3.1 Procedure

Subjects stood straight facing the lifting box adjusted to the elbow high. Each subject had to perform the pilot test and the experiment trial in two different sessions. During the pilot test, the subject's verbal evaluation regarding the sensation of fatigue in the upper extremity, the lower extremity and the whole body was done. In the second session, the experiment was performed. The subjects had to perform 24 sets of squats with ten seconds interval between each squat. Same three regional sensation of fatigue was evaluated in the trial. Along with the perceived exertion, the EMG signals and the heart rate was monitored.



<Figure 1> Symmetric Lifting and Lowering of the Lifting Box [1]

3.2 Statistical Analysis

For the Borg Scale readings of the perceived exertions intra-class correlation coefficient was used for test-retest reliability, (ICC index 0.71~0.86). <Table 1> shows the statistical summary of the RPEs of the lower and upper extremity. For the mean power frequencies, the normality check was performed on each muscle. Significance of each variable was checked. Hosmer-lemeshow test was performed on the model to check if it performs well for the predicted outcome. Deviance of each outcome was plotted against fitted probability to check how well fatigued and non-fatigued

<Table 1> Statistics Summary for Rates of Perceived Exertion

Squat set	Ratings of Perceived Exertions			
	Upper extremity		Lower extremity	
	Average	Std Dev	Average	Std Dev
4	2.32	1.06	2.04	0.89
8	2.96	0.97	3.32	0.85
12	3.44	0.89	3.92	0.75
16	3.92	0.98	4.48	0.824
20	4.52	0.98	5.56	0.926
24	5.32	1.12	5.96	0.955

3.3 Model Development

Main aim of the study was to combine the effect of physiological indicators of fatigue which include the normalized mean power frequency from the eight major muscles of upper and lower extremity, the heart rate and the psychological indicators such as ratings of perceived exertion. There effect to perceive whole body fatigue was to be modeled as dichotomous variable. For this purpose value of RPE > 4 on Borg CR-10 scale for whole body fatigue was considered in fatigue category while for the RPE. Therefore a model was made to predict the whole body fatigue and the determining the appropriate variables that are significant to the changes in whole body fatigue.

One of the multivariable approach used to model multivariable problem is to use the logistic regression modeling. For this purpose, the logit function was used for the model development. The logistic regression for binary response fits a logistics curve y = f (x) for the relation between the binary outcome and all the variables. The curve usually starts with a very small slope and then increases exponentially followed by steady decrease in the end. As the dependent variable in this study was categorical therefore, the binary logistic regression was used to predict the fatigued and non-fatigued. A total of nine independent variables were used for the binary logistic regression. Which includes the NMPF from the eight muscles, heart rate and the Borg scale readings from the upper and lower extremity of the body. The probability of occurrence of an event is given by the following equation

$$\hat{p} = \frac{e^{\beta_0+\beta_1 X_1 \cdots\cdots+\beta_k X_k}}{1+e^{\beta_0+\beta_1 X_1 \cdots\cdots+\beta_k X_k}} \tag{1}$$

Where

$\hat{p}$ = probability of event of interest
β_0 = constant
β_1 = coefficient of independent variable X_1
k = total number of features.

Equation one was used to find the probability of fatigued subjects as given below

$$p(\hat{f}) = \frac{e^{y'}}{1+e^{y'}} \tag{2}$$

For performing the logistic regression following the coefficients of all the features were determined.

MPF_{md}	Mean Power Frequency of Medial Deltoid Muscle
MPF_{ad}	Mean Power Frequency of Medial Anterior Deltoid
MPF_{ut}	Mean Power Frequency of Medial Deltoid Upper Trapezius
MPF_{sp}	Mean Power Frequency of Supraspinatus
MPF_{bf}	Mean Power Frequency of Medial Bicep femoris
MPF_{vs}	Mean Power Frequency of Vastus Laterlis
MPF_{gs}	Mean Power Frequency of gastrocnemius
MPF_{rf}	Mean Power Frequency of Rectus Femoris
RPE_U	Rate of perceived exertions for upper extremity
RPE_L	Rate of perceived exertion for lower extremity
HR	Heart rate

Equation 3 shows the 11 independent varies along with the coefficients to be determined through logistic regression modeling.

$$\begin{aligned} y' = {} & \beta_0+\beta_1 MPF_{md}+\beta_2 MPF_{ad}+\beta_3 MPF_{ut}+\beta_4 MPF_{sp} \\ & +\beta_5 MPF_{bf}+\beta_6 MPF_{vs}+\beta_7 MPF_{gs}+\beta_8 MPF_{rf} \\ & +\beta_9 RPE_U+\beta_{10} RPE_L+\beta_{11} HR \end{aligned} \tag{3}$$

4. Results

The coefficients where found (<Table 2>) and it was observed that among the mean power frequencies for the upper and lower extremity the anterior deltoid and the bicep femoris had the greatest absolute values of the coefficient respectively. For the ratings of perceived exertions of the upper and lower extremity, the lower extremity was observed to have greatest coefficient. The significance level of each variable was checked to see which variable is more significant in predicting the response variable. It was observed that the mean power frequency of anterior deltoid, the rate of perceived exertion of the upper and lower extremity were found to be significant.

However, the odds ratio was also taken under consideration and it was observed that among the muscles, the AD, VS and the RF muscles had ratios greater than one with AD and RF having very high odd ratio. By looking at the p values, the RF and the VS muscles having not significant p values but as the purpose of the p value is how likely we expect the more extreme data then the observed data under the model with given restrictions. The odds ratio is also considered for this mode. Considering the coefficients, among the muscles of upper extremity the anterior deltoid has the highest coefficient, among the lower extremity the bicep femoris has the highest coefficient while the heart rate also has high coefficient.

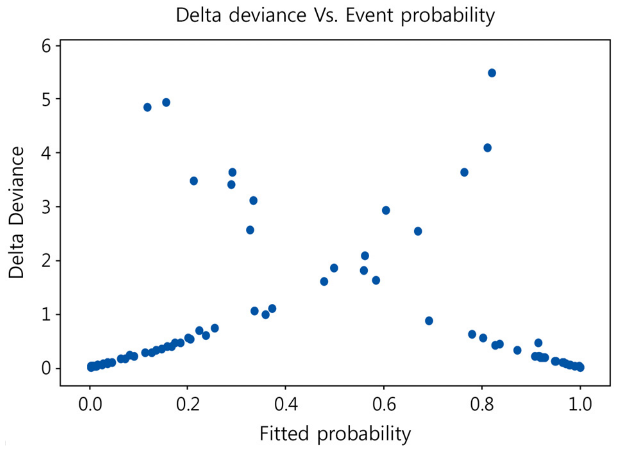
<Table 2> Coefficients of Variables and Significance

Variable	Coefficient	Chi-square	p-value
MPF_{md}	-3.48	0.54	0.464
MPF_{ad}	16.87	14.82	0.01*
MPF_{ut}	-3.37	0.85	0.356
MPF_{sp}	-4.75	1.17	0.280
MPF_{bf}	-5.25	0.82	0.367
MPF_{vs}	1.68	0.30	0.582
MPF_{gs}	-3.26	0.69	0.406
MPF_{rf}	2.81	1.33	0.249
RPE_U	2.038	8.71	0.01*
RPE_L	2.653	51.33	0.01*
HR	5.47	0.63	0.428

*$p < 0.01$.

The delta deviance graph in <Figure 2> shows the difference between the experimental value and the values predicted by the model fit. Each data point has been plotted against its probability. The event probabilities for the fatigued and the non-fatigued state are shown in the curves.

The curve from top left to bottom right shows that there is a high probabilities of event as fatigued at bottom right. The curves show a low probability at the top left to be detected as non-fatigued The curve from top left to the bottom right represents the fatigued subjects while the curve from the top right to the bottom left represents the non-fatigued subjects. Both represents good fits as both have low delta deviance for fatigued and non-fatigues states.



<Figure 2> Delta Deviance Plotted Against the Event Probability

The model accuracy was checked for both fatigued and non-fatigued state. When fatigue was incorporated as event of interest in the model, the accuracy was 83% while for the non-fatigued subjects as main event, the accuracy was 93%. The percent of event detected as non-fatigued in fatigue as main event was 9% and for fatigued in non-fatigued event was 17%. The hosmer-lemeshow test was performed ($p > 0.05$) which is a strong finding that the model fits well.

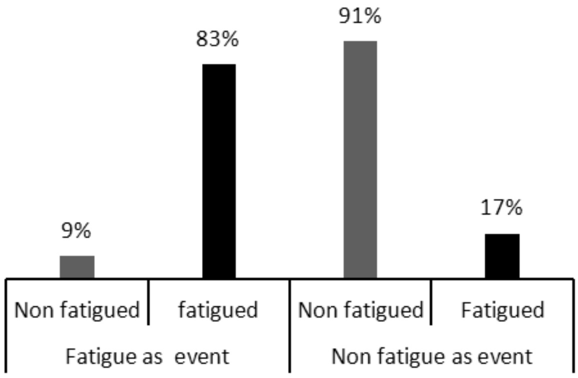
5. Discussion sign

This study was an attempt to model whole body fatigue which is the first indicator by the subject to experience fatigue. The model combined eleven different variables from major perceived regions of the body. The modeled showed a high accuracy of 83% and 91% in fatigued and non-fatigued subjects respectively. In particular it was observed the perceived upper and lower extremity perceived exertions and the NMPF of the anterior deltoid were the most significant variables in the logistic regression modeling. This study provides advantage of combining different types of features used as indicators of fatigue rather than single type of feature as done by previous studies. Secondly the dichotomous response help in easy interpretation which has been used as perceived whole body fatigue [3].

The overall purpose of this study was to find the effect of contributing physiological and perceived indicators of fatigue on whole body fatigue. Fatigue related musculoskeletal disorders are important concern in different manufacturing environments, therefore its monitoring needs to be as accurate as possible. Borg [6] in his regard attempted to quantify the perceived exertion. Most of the studies that used Borg and other variables used a pre-defined setting to keep the muscle activity as constant as possible across all he subjects, such as cycle ergometer [10]. These clinical settings often tend to focus on one type of muscle and neglect the effect of different indicators contributing to whole body fatigue [5, 13]. However there are few studies that involve integration of multiple fatigue indicators modeled to develop fatigue monitoring system driven by the data obtained through wearable sensors [28].

For this study, the Mean power frequencies of eight major muscles, heart rate and the Borg rating of perceived exertion was used in logistic regression. To our knowledge, no other studies have used these variables for dynamic squat lifting. Therefore, the dynamic squat lifting was simulated in lab for 24 sets of squats on 25 subjects. The dependent variable, which was a dichotomous variable representing the whole body fatigue provided vital results that can be used to develop work rest framework and help in prevention of musculoskeletal disorders. All the coefficient of the independent variables that represents the best model fit were shown in <Table 2>. Previous mostly used only EMG or ratings of perceived exertion alone to assess fatigue [11, 17, 14, 33].

The logistic regression modelling used for this study yielded high accuracy for both fatigued and non-fatigues states as shown in <Figure 3>. Different studies have used different modeling approaches such as the three compartment approach [18], dynamic modelling [19] or decision tree approach [25]. Main reason is that EMG data contains log of noise and the signal to noise ratio is quite high. Not only in the power frequency variable but also in the perceived response. In such cases, the logistic regression performs better than the decision tree. Another advantage of using logistic regression for this fatigue detection model is that the linear relation between the whole body fatigue and other 11 variables have not to be considered. The logistic regression handles the nonlinear



<Figure 3> Probability of Detecting Fatigue and Non-Fatigue Events Under Two Different Conditions

relation between the dependent and independent variable in a much better way.

The study has some limitations as it took into account only male population, the perceived female effort might be different. However as this study was focused on the manufacturing sector, which is being dominated by the male population globally, therefore only male subjects were considered. Among the two lifting techniques of stoop and squat lifting, this study included squat lifting, therefore stoop lifting will generate different results. However this study was designed to incorporate major muscle therefore squat lifting was introduced. For the grip of the lifting box proper lifting handles were used which in some cases might differ while lifting therefore some discrepancies in the results may occur regarding the change of grip conditions.

6. Conclusion

The logistic regression modeled perceived whole body fatigue with a total of 11 number of independent variables. The mean power frequency of the anterior deltoid muscle, the rectus femoris and the perceived lower extremity were found to be significantly effecting the perceived whole body fatigue. The model can be used in applied ergonomics for designing rest/work schedules and prevention of musculoskeletal disorders.

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