Total perceived discomfort function for upper limbs based on joint moment

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Abstract. The aim of this study was to formulate a relationship between the total perceived discomfort of the upper limbs and the perceived discomforts of each degree of freedom (DOF). The biomechanical analysis was performed based on classifying the posture and load via rapid upper limb assessment (RULA). The summary scores of the RULA and the perceived discomforts of each DOF were the objective and explanatory variables, respectively. Four approximation models (average, maximum, hybrid, and radial basis function (RBF) network) were compared in terms of accuracy in predicting the total perceived discomfort. In conclusion, among the four models, the RBF network provided the highest accuracy, followed by the hybrid model.

Keywords: Ergonomics, Biomechanics, Perceived discomfort, Rapid upper limb assessment, Evaluation function, Function approximation

1. Introduction

Physical workloads should be evaluated quantitatively and objectively to design work environments that minimize the workload and prevent musculoskeletal disorders. In addition, the time allocated to improve work environments is decreasing each year with the shortening of product development period. Therefore, an ergonomic physical load evaluation must be performed effectively in a short amount of time. Biomechanical analysis evaluates the physical load based on the equilibrium of force using a rigid link model of the human body \cite{1}. The reactive moment on each joint against external forces (hereafter referred to as “the joint moment”) is regarded as the indicator of physical load \cite{2, 3}. The joint moment can be calculat-
ed by computer simulations, such as commercial digital human software [4]. Therefore, the evaluation of work environments using biomechanical analysis can be applied for efficient ergonomic designs [5, 6].

Both the objective physical load and the subjective discomfort should be quantified and minimized to optimize work environments for laborers [7]. Therefore, the relationship between the objective joint moment and the subjective perceived discomfort was investigated. Researchers investigated this relationship for various human joints [8, 9, 10, 11]. In our previous study, we formulated a relationship between the perceived discomfort and the joint moment for twelve joint motion directions of the upper limbs [12]. The target joint motions were the six directions of the shoulder joint (i.e., extension, flexion, adduction, abduction, internal rotation, and external rotation), two directions of the elbow joint (i.e., elbow extension and elbow flexion), and four directions of the wrist joint (i.e., wrist extension, wrist flexion, wrist ulnar deviation, and radial deviation). The discomfort functions of each joint motion direction were approximated using a logistic function. However, these previous studies on the joint moment did not investigate the evaluation method for the total perceived discomfort of multiple joint moments. For example, two design solutions, A and B, can be considered for the case of multiple joint moments. Solution A produces a higher amplitude of shoulder joint moment and a lower amplitude of elbow joint moment; conversely, solution B produces a lower shoulder joint moment and a higher elbow joint moment. In this situation, there is a trade-off between the shoulder and elbow joint moments; thus, it is difficult for designers to determine a preferable solution. Therefore, the total perceived discomfort function must be formulated so as to determine the ideal solution of the order of multiple design solutions for work environments.

Several observational methods are used to assess the total physical workload [13, 14]. For example, the rapid upper limb assessment (RULA), Ovako working posture analysing system (OWAS), and rapid entire body assessment (REBA) evaluate the total workload of the upper limb or the entire body [15, 16, 17]. In these methods, the positions of the individual body segments and the weight of the load handled are observed and scored with a worksheet, and the total workload is calculated from the summary scores. These methods are straightforward, and they are widely used by professional ergonomists. However, they cannot perform detailed evaluations of the total workload because the worksheets only roughly classify the postures of workers and the lifting of weights. In OWAS, for example, the posture of the upper limb is classified as either higher or lower than the shoulder joint. Each classified category in the worksheet covers a relatively wide range of body segment postures and handling loads. Thus, it is possible for different postures to have a measurable difference of the total workload even if the postures are classified into the same category and have the same summary scores. In addition, the observation methods consider the weight of the load handled, but they do not consider the direction of the force except the gravitational direction. In real
situations, arbitrary external forces will act on the human body. However, the loading conditions of the traditional observation methods cover only limited situations.

The evaluation based on the joint moments can detail the total workload of arbitrary human postures and external forces if the total perceived discomfort function is first formulated. Thus, the objective of the present study was to determine the best approximation model for the total perceived discomfort function among four models that will be proposed below. In this study, we focused on the upper limbs, as in the previous study [12], and the total perceived discomfort function was approximated using RULA. The biomechanical analysis was performed based on the classification of the postures and the load conditions from RULA, enabling the calculation of the joint moments of each degree of freedom (DOF). Then, the perceived discomforts of each DOF were obtained by applying the perceived discomfort function proposed in the previous study [12]. The summary scores of RULA were established as the objective variables, and the perceived discomforts of each DOF were established as the explanatory variables. The response surfaces of the total perceived discomfort were approximated by four different models: average, maximum, a hybrid of average and maximum, and radial basis function network (RBF) [18]. The accuracy of the response surfaces was compared to determine the proper approximation model.

2. Methods

2.1. Selection of calculation conditions from RULA

The calculation conditions for the biomechanical analysis (i.e., the posture of the upper limb and the weight of the load) were determined based on the posture and the load classification of the RULA. In the RULA method, the sub-summary scores were calculated for the two groups: the arm and the wrist (Group A) and the neck, trunk, and legs (Group B). Next, the summary score was determined by the sum of the two sub-summary scores. In this study, we focused on the total perceived discomfort of the upper limbs; hence, the criteria of Group A in RULA were used to select the calculation conditions. The calculation of the sub-summary score for Group A consisted of four parts regarding the upper limb posture (i.e., the upper arm position, lower arm position, wrist position, and wrist twist), one part regarding the duration of muscle use, and one part regarding the amplitude of the load. Each part had several ranges that were assigned a score, as shown in Fig. 1. First, the score for the posture part was determined based on the worksheet shown in Fig. 1. The scores for the duration of muscle use and the loading amplitude were added to the posture score, resulting in the sub-summary score for the upper limb.

In this study, the levels of each part for the biomechanical analysis were determined as shown in Table 1. Among the six parts of Group A, the wrist twist and the duration of muscle use were both ignored because these conditions were not considered in the previous study [12]
(i.e., the wrist was not twisted and the duration of force exertion was only 10 s). With respect
to the remaining four parts, we selected values in the center of the ranges for the calculation
conditions. In addition, to efficiently evaluate all RULA scores, only one condition was se-
lected when multiple conditions had the same score.

For the case of the upper arm position, it has five flexion/extension angles and three
add/subtract conditions (i.e., the shoulder elevation, abduction of the upper limb, and sup-
porting of the upper arm). Among the three add/subtract conditions, the shoulder elevation
and the supporting of the upper arm were ignored because they were not considered in the
previous study [12]. The abduction angle of the upper limb was assumed to be 45°, and the
upper arm position was evaluated at five levels, as shown in Table 1. For the lower arm posi-
tion, the add condition was set to a 40° internal rotation of the shoulder joint, and the three
levels are listed in Table 1. For the wrist position, the add condition was set to a 30° ulnar de-
viation of the wrist joint, and the four levels are listed in Table 1. Lastly, for the loading am-
plitude, the load was assumed to be a static load and the three levels are listed in Table 1.
Thus, there were 180 calculation conditions. The sub-summary score of the calculation con-
ditions ranged from 1 to 10. In this study, the sub-summary score was normalized to [0, 1],
and the normalized score was the objective variable for the function approximation.

![Figure 1: RULA sheet for the arm and wrist (Group A) [15]](image-url)
2.2. Biomechanical analysis for selected conditions

The outline of the joint moment derivation in biomechanical analysis is described as follows. Figure 2 shows the two segments upper limb model, and the model assumes that the lower arm and the hand are one segment for the purpose of illustration. The moment which amplitude equals to \((M_f L_f + M_p L_p)g\) acts on the elbow joint. To keep the posture shown in Fig.2, the elbow joint exert a moment that has the same amplitude and opposite direction to the external moment. This is the joint moment, and it is regarded as the indicator of physical workload.

The biomechanical analyses were conducted for the selected 180 conditions to calculate the joint moments for each DOF of the upper limbs. The biomechanical model for the analysis was constructed based on the 50 percentile of Japanese male [19]: a height of 171 cm and a weight of 63.7 kg. The length and weight of each body segment were determined based on previous research [1]. The joint moments for each DOF were calculated, and then the calculated joint moments were divided by the maximum joint moment of each DOF to obtain the joint moment ratio \(r\) \((r = [0, 1])\). Here, the maximum joint moments a human can exert were quoted from Chaffin et al. [1] and the National Institute of Technology and Evaluation [20]. The perceived discomfort of each joint motion direction was calculated by the following equations [12]:

\[
f_i(r) = \frac{0.986}{1 + \exp \left[-7.56(r - 0.354)\right]} \tag{1}
\]
where \( f_1 \) denotes the perceived discomfort scores for all movements except the elbow flexion, and \( f_2 \) denotes the perceived discomfort score for the elbow flexion. In addition, \( f_1 \) and \( f_2 \) range from 0 to 1; a higher score indicates a higher physical load. In this study, the upper limb has 6 DOF: the three DOF of the shoulder joint (i.e., extension/flexion, adduction/abduction, and internal rotation/external rotation), one DOF of the elbow joint (i.e., extension/flexion), and two DOF of the wrist joint (i.e., extension/flexion and ulnar deviation/radial deviation). Therefore, the perceived discomforts of six DOF were calculated.

Figure 2: Two segments upper limb model and calculation of elbow joint moment

### 2.3. Approximation models of total discomfort function

The total perceived discomfort likely increases as the perceived discomfort of each DOF increases. We assumed that the total discomfort is dominated by the average value of discomfort for each DOF over the range of relatively low discomfort for each DOF. However, the total discomfort was dominated by the maximum value of discomfort for each DOF over the range of relatively high discomfort for one or more DOFs. In addition, the relationship between the total discomfort and the discomforts of each DOF is possibly a weakly nonlinear function. Therefore, in this study, four function approximation models were used: average model, maximum model, hybrid model of the average and maximum models, and RBF network. Among the four models, the average model and the maximum model are defined as follows, respectively:

\[
T = \frac{a \cdot \sum_{i=1}^{6} w_i}{6} \quad (3)
\]

\[
T = a \cdot \max_i w_i \quad (4)
\]
where $T$ and $w_i$ denote the total perceived discomfort (i.e., the objective variable) and the perceived discomfort of the $i$-th DOF (i.e., the explanatory variable), respectively, and $\alpha$ is the regression coefficient. The normalized sub-summary score of RULA was the objective variable, and the perceived discomforts of the upper limb were the explanatory variables. The regression coefficient was obtained by the least-square method.

The hybrid model was defined as follows:

$$T = (1 - \alpha) \cdot \frac{1}{6} \sum_{i=1}^{6} w_i + \alpha \cdot a_2 \cdot \max_i w_i$$  \hspace{1cm} (5)

$$\alpha = \frac{1}{1 + \exp \left( b \left( \max_i w_i - c \right) \right)}$$  \hspace{1cm} (6)

In Eq. (5), the first and second terms of the right side represent the average and maximum models, respectively. $a_1$ and $a_2$ are the regression coefficients of the average and maximum terms, respectively. In addition, $\alpha$ represents the transition parameter of the average and maximum terms, and $b$ and $c$ are the regression coefficients. As shown in Fig. 3, the transition parameter $\alpha$ increases as the maximum perceived discomfort increases. Therefore, $\alpha$ in Eq. (5) indicates the rate of influence the maximum perceived discomfort of each DOF has on the total discomfort. When the maximum perceived discomfort of each DOF was relatively low, the transition parameter was also low and the total perceived discomfort was dominated by the average discomfort. Conversely, when the discomfort of each DOF was relatively high, the transition parameter was also high and the total perceived discomfort was dominated by the maximum discomfort.

The RBF network performed well in terms of accuracy and robustness, irrespective of the degree of nonlinearity [21]. A detailed procedure for constructing a response surface using the RBF network is provided in the Appendix.

![Diagram of transition parameter with respect to maximum perceived discomfort](image-url)
In addition to computing all the calculation conditions, the response surfaces were approximated for two groups of calculation conditions. These were divided based on the amplitude of discomfort values of each DOF in order to confirm the assumption that the total discomfort depends on the amplitude. In this study, the calculation conditions were divided into the low discomfort group when the discomfort scores of each DOF were below 0.5, and the high discomfort group when one or more discomfort scores exceed 0.5.

2.4. Determination of optimal model

The accuracy of the four response surfaces were compared using the average absolute error (AAE). The AAE for the \( i \)-th function model was calculated as follows:

\[
AAE_i = \frac{\sum_{j=1}^{n} |T_j - \hat{T}_{ij}|}{n} \tag{7}
\]

where, \( T_j \) and \( \hat{T}_{ij} \) denote the normalized sub-summary score and the approximated total perceived discomfort for the \( j \)-th calculation condition of the biomechanical analysis, respectively. \( n \) is the number of calculation conditions that are used for constructing the response surfaces; thus, \( n = 180 \) when the all calculating conditions are used. The AAEs of the response surfaces are compared among the four approximation models. One-way ANOVA was conducted at a significance level of 5% and Tukey’s post-hoc tests were carried out to compare the four models.

3. Results

A biomechanical analysis was performed based on the calculation conditions shown in Table 1. Here, the number of data in the low discomfort group (max \( w_i \leq 0.5 \)) and the high discomfort group (max \( w_i > 0.5 \)) were 77 and 103, respectively. The total perceived discomfort was predicted by calculating the data from the low group, high group, and both groups. Table 2

<table>
<thead>
<tr>
<th>Approximation models</th>
<th>Regression coefficients</th>
<th>Low discomfort group</th>
<th>High discomfort group</th>
<th>Both groups</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( a )</td>
<td>3.53</td>
<td>1.70</td>
<td>1.79</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum</td>
<td>( a )</td>
<td>1.86</td>
<td>0.745</td>
<td>0.783</td>
</tr>
<tr>
<td></td>
<td>( a_1 )</td>
<td>4.40</td>
<td>11.7</td>
<td>4.55</td>
</tr>
<tr>
<td>Hybrid</td>
<td>( a_2 )</td>
<td>1.28</td>
<td>0.728</td>
<td>0.729</td>
</tr>
<tr>
<td></td>
<td>( b )</td>
<td>-19.4</td>
<td>-14.3</td>
<td>-8.54</td>
</tr>
<tr>
<td></td>
<td>( c )</td>
<td>0.263</td>
<td>0.405</td>
<td>0.345</td>
</tr>
</tbody>
</table>
Figure 4 and Table 3 show the accuracy of the four approximation models. The ANOVA results show that there is the main effect of approximation model irrespective of the data set. Among the four models, the AAE of the RBF was the lowest, followed by the hybrid model. The AAEs of the RBF and hybrid models for the all conditions were approximately 0.08 and 0.10, respectively, whereas the AAEs of the average and maximum models were both approximately 0.17. For the case of low discomfort, there was no significant difference between the average and maximum models. In contrast, for the case of high discomfort, the AAE of the maximum model is lower than that of the average model within a significance of 1%.

Table 3: Average absolute error and maximum error of four approximation models

<table>
<thead>
<tr>
<th>Items</th>
<th>Approximation models</th>
<th>Low discomfort group</th>
<th>High discomfort group</th>
<th>Both groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.120</td>
<td>0.149</td>
<td>0.169</td>
</tr>
<tr>
<td>Maximum</td>
<td></td>
<td>0.140</td>
<td>0.108</td>
<td>0.164</td>
</tr>
<tr>
<td>Hybrid</td>
<td></td>
<td>0.090</td>
<td>0.098</td>
<td>0.104</td>
</tr>
<tr>
<td>RBF</td>
<td></td>
<td>0.065</td>
<td>0.058</td>
<td>0.077</td>
</tr>
<tr>
<td>Maximum error</td>
<td></td>
<td>0.419</td>
<td>0.553</td>
<td>0.610</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.413</td>
<td>0.337</td>
<td>0.512</td>
</tr>
<tr>
<td>Maximum</td>
<td></td>
<td>0.306</td>
<td>0.325</td>
<td>0.329</td>
</tr>
<tr>
<td>RBF</td>
<td></td>
<td>0.227</td>
<td>0.204</td>
<td>0.287</td>
</tr>
</tbody>
</table>
Moreover, for the case of all the calculation data, the AAEs of the average and maximum models are approximately the same. In addition, as shown in Fig. 3, the regression coefficient $c$ in Eq. (6) indicates the dividing point between the range dominated by the average discomfort and that dominated by maximum discomfort; the parameter $c$ equals 0.345, as depicted in Table 2.

4. Discussion

4.1. Influence of amplitude of perceived discomfort

According to Fig. 4, in the range that the discomfort values of the DOFs were relatively low, the total discomfort may be more affected by the average of the discomfort values of each DOF than by the maximum value of them. In addition, the total discomfort was most affected by the maximum discomfort value of each DOF over the range of high discomfort values of the DOF. This is consistent with the premise that the relationship between the total discomfort and the discomfort values of each DOF varies with respect to the amplitude of the discomfort. Therefore, the proposed hybrid model outperforms the average and maximum models, especially when the perceived discomfort of each DOF encompassed a wide range. In addition, the regression coefficient $c$ in Eq. (6) equals to 0.345; thus, the dominating factor of the total perceived discomfort gradually transitions from the average discomfort to the maximum discomfort when the maximum discomfort exceeds approximately 35% of the scale of the perceived discomfort.

4.2. Comparison of approximation models

The RBF provided the best accuracy among the four models, irrespective of the amplitude of perceived discomfort. The RBF predicted nonlinear functions with high accuracy; therefore, the relationship between the total perceived discomfort and the discomforts of each DOF is nonlinear. In addition, the hybrid model has the second lowest AAE after the RBF, irrespective of the amplitude of perceived discomfort. We determined that the response surfaces predicted by the RBF and hybrid model have a sufficient accuracy. Among the four approximation models, the RBF and hybrid models were the preferable approximation methods for the total perceived discomfort function.

4.3. Validation of approximation models

To validate the accuracy of the response surfaces with a limited number of data, the $k$-fold cross-validation method was used [22, 23]. In this method, the data set is divided into $k$ groups, and the response surface is developed using the data of $(k - 1)$ groups out of $k$ groups (i.e., the training set). Next, the AAE of the other group (i.e., the testing set) is calculated.
This procedure is performed for each of the $k$ groups, and the average AAE is calculated as the approximation accuracy for unknown data. In this paper, the 180 data were randomly divided into 10 groups, and a 10-fold cross-validation was applied to all four approximation models. One-way ANOVA was conducted at a 5% significance, and Tukey’s post-hoc tests were carried out to compare the four models.

Figure 5 shows the results of the cross-validation. The AAE of the cross-validation has the main effect of approximation model. In addition, the RBF network had the lowest AAE, followed by the hybrid model. Both AAEs of the RBF and hybrid models were significantly lower than those of the average and maximum models. In addition, the AAEs of the cross-validation were approximately the same as the AAEs when using all conditions (i.e., 180 calculation conditions). Therefore, the RBF and hybrid models were both appropriate for expressing the total perceived discomfort.

![Figure 5: Results of cross-validation: comparison of AAE among the four approximation models ** p < 0.01](image)

5. Conclusions

In this study, function approximation models for the total perceived discomfort of the upper limb was investigated. The training data set for function approximation was constructed based on RULA, and the four approximation models (average, maximum, hybrid, and RBF) were used to predict the total perceived discomfort. The major findings are as follows:

1. In the range that the discomforts of each DOF are relatively low, the total perceived discomfort is dominated by the average discomfort of each DOF. Conversely, in the range that the discomforts are relatively high, the total perceived discomfort is dominated by the maximum discomfort of each DOF. The dominant factor of the total discomfort transitions when the maximum discomfort exceeds approximately 35% of the scale of perceived discomfort.

2. Among the four function approximation models, the AAE of the RBF is the lowest fol-
lowed by the hybrid model, irrespective of the data set. Therefore, the relationship between the total perceived discomforts and the discomfort of each DOF’s is nonlinear, and the RBF and hybrid models are the preferred approximation models to the average and maximum models.

The total perceived discomfort function predicted by the RBF network or the hybrid model is the objective function for the work environment design when the physical load of the upper limb is the main determinant factor. The discomfort values of each DOF can complicate the determination of an optimum work environment because there is a trade-off between the discomfort values. However, the total perceived discomfort function is a unique criterion, and the optimum work environment can be obtained by minimizing the function.

Acknowledgement
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Appendix A. Radial Basis Function Networks
The RBF network [18] is a type of neural network that yields a response surface via a superposition of basis functions. The output of the RBF network is given by the following equation:

$$O(x) = \sum_{j=1}^{m} w_j h_j(x)$$

(A.1)

where $x = \{x_1, x_2, \ldots, x_n\}^T$ is a design variable vector, $n$ is the number of design variables, $w_j$ is the weight for $h_j(x)$, and $m$ is the number of training data. $h_j(x)$ is an RBF given by

$$h_j(x) = \exp \left( -\frac{\|x - c_j\|^2}{r_j^2} \right)$$

(A.2)

where $c_j$ and $r_j$ are the center and the radius, respectively, of the $j$-th basis. In this study, $r_j$ is given by the following equation [24]:

$$r_j = \frac{d_{j,\text{max}}}{\sqrt{n/2m-1}}$$

(A.3)

where $d_{j,\text{max}}$ denotes the maximum distance between the $j$-th training data and another training data in the training set. The learning of the RBF network involves obtaining appropriate weights for each basis and is identical to the energy minimization of the RBF network. The energy of the RBF network is given by

$$E = \sum_{j=1}^{m} (y_j - O(x_j))^2 + \sum_{j=1}^{m} \lambda_j w_j^2$$

(A.4)

where $y_j$ is training data at the sampling point $x_j = \{x_{j1}, x_{j2}, \ldots, x_{jn}\}^T$ and $\lambda_j$ is a regularization parameter whose value is 0.01 in this study [25]. The optimal weight vector $w = \{w_1, w_2, \ldots,$
$w_m^T$ is given by the following equation:

$$w = (H^T H + A)^{-1} H^T y$$ (A.5)

where $H$, $A$, and $y$ are given by

$$H = \begin{bmatrix}
    h_1(x_1) & h_2(x_1) & \cdots & h_m(x_1) \\
    h_1(x_2) & h_2(x_2) & \cdots & h_m(x_2) \\
    \vdots & \vdots & \ddots & \vdots \\
    h_1(x_p) & h_2(x_p) & \cdots & h_m(x_p)
\end{bmatrix}$$ (A.6)

$$A = \begin{bmatrix}
    \lambda_1 & 0 & 0 & 0 \\
    0 & \lambda_2 & 0 & 0 \\
    \vdots & \vdots & \ddots & \vdots \\
    0 & 0 & 0 & \lambda_m
\end{bmatrix}$$ (A.7)

$$y = \begin{bmatrix}
    y_1 \\
    y_2 \\
    \vdots \\
    y_p
\end{bmatrix}^T$$ (A.8)

In this way, the main procedure of obtaining the results is calculating the inverse matrix. Therefore, the RBF network can be evaluated quickly, and additional analysis can be easily conducted when new data sets are added.

References


