Developing Joint-level Scoring Models Tailored to Whole-body Ergonomic Assessment of Construction Workers

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Abstract –

Construction workers frequently engage in manual operations at workplaces, increasing their ergonomic risks of developing Work-Related Musculoskeletal Disorders (WMSDs). To proactively assess and prevent such risks, ergonomic scales have been widely employed, incorporated cutting-edge technologies to achieve advancements in automation. However, these scales have demonstrated limited accuracy in risk identification, mainly attributed to unreliable joint-level assessment rules based on discrete boundaries and binary rules. Although previous attempts have incorporated fuzzy logic to improve accuracy, the involved subjective determination of function shapes and threshold settings remains a persistent hindrance. To address this limitation, the present study aims to develop data-driven joint-level scoring models for replacing these conventional rules. This process leverages pose data from the Construction Motion Data Library (CML) dataset and employs a robust and heuristic data-driven approach named Heuristics Gaussian Cloud Transformation (H-GCT). The results, with all Confusion degrees below the threshold value of 0.64, demonstrate the significant independence of the developed scoring models, ensuring accurate identification of ergonomic risk. Furthermore, a comparison is conducted with previous studies that employed fuzzy logic to improve REBA. This process highlights the superiority of the data-driven H-GCT in developing scoring models. This study contributes to the existing body of knowledge by providing joint-level scoring models to improve the applicability of ergonomic assessment in construction. Future studies can further enhance this work by expanding pose data, enriching assessment modules, and refining the data-driven approach.

Keywords –

Postural ergonomic risk assessment; Data-driven approach; WMSDs prevention; Occupational health and safety

1 Introduction

Construction workers frequently engage in physically demanding manual operations at workplaces [1]. As a result, they face remarkable ergonomic risks of developing Work-Related Musculoskeletal Disorders (WMSDs). In Hong Kong, statistics from the Pilot Medical Examination Scheme (PMES) reveal that around 41% of registered construction workers suffer from WMSDs-related injuries [2]. Moreover, amidst the challenges posed by an aging labor force, escalating labor wage, and manpower shortages in construction, ergonomic risks may give rise to increasingly serious repercussions. Therefore, it is crucial to assess and prevent ergonomic risks of workers' operations.

To proactively prevent ergonomic risks for construction workers, various systematic observation methods have been employed. These methods typically involve the assessment by experienced experts and incorporate observational ergonomic scales such as Rapid Entire Body Assessment (REBA) [3], Rapid Upper Limb Assessment (RULA) [4], and Ovako Working Postures Assessment System (OWAS) [5]. Serving as assessment tools, these scales define the rules for coding posture-related data (e.g., joint angles) and subsequently rate ergonomic risks for construction workers based on the data [6]. For instance, REBA codes the postures of the trunk, neck, legs, upper arms, lower arms, and wrists, while assigning whole-body postures with ergonomic risk scores ranging from 1 to 15.

However, attributed to manual implementation, these practical methods are subject to notable constraints in objectivity and cost-effectiveness. To address these challenges, recent advancements have introduced cutting-edge data collection technologies, such as computer vision [7] and wearable sensors [8], to enable automated detected of ergonomic risks. In line with these initiatives, several studies have adopted machine learning and deep learning algorithms to classify postural ergonomic risks. For example, Zhang, Yan [9] compared the accuracy of multiple classification algorithms (BP-

ANN, DT, SVM, KNN, and EC) and developed optimal posture classifiers for the arms, back, and legs. Moreover, from the perspective of whole-body posture, Antwi-Afari, Qarout [8] trained a gated recurrent units (GRU) network to accurately classify five types of awkward working postures. However, an evident limitation emerges as the insufficient interpretability regarding the relationship between inputs and outputs in these black-box classification methods, particularly in comparison to risk rating based on well-established rules. In response to this challenge, a significant body of research transfers 2D [10] or 3D [7] joint coordinates extracted by pose estimation technologies into joint parameters. These joint parameters further serve as inputs for ergonomic scales such as REBA.

Despite significant progress in automated implementation of ergonomic scales, these scales have demonstrated limited accuracy in assessing ergonomic risk for construction workers [11]. This limitation is primarily attributed to the unreliable rules for joint-level assessment. Specifically, these scales rely on discrete boundaries and binary rules (specified angle ranges and positions) to determine risk categories for assessed modules [3, 4]. However, the formulation of these ranges for classifying joint-level risks lacks reliable support by statistical data on joint angles obtained from construction workers [12]. Furthermore, the oversimplified binary rules are susceptible to subjectivity resulting from manual observations and errors introduced by the pose estimation tools. Despite attempts to improve the joint-level rules by fuzzy logic [11, 13], the subjective determinations of function shapes and transition ranges continue to hinder the accuracy. Therefore, the development of joint-level scoring models, utilizing extensive 3D pose data of construction workers and a robust data-driven algorithm, holds potential for improvement. This approach allows for proactive mining of implicit knowledge from voluminous data and effectively captures the characteristics of variations in joint-level risks [14, 15], thereby enhancing the credibility of scoring models.

To address the limitation in joint-level assessment rules of ergonomic scales, this study attempts to develop data-driven scoring models for replacing the unreliable discrete boundaries and binary rules. Given the objectivity of the REBA scale, which scores ergonomic risks based on joint angle values [7], and its emphasis on whole-body assessment covering critical body segments such as the trunk, neck, legs, upper arms, lower arms, and wrists, the joint-level modules of REBA serve as the foundational framework in this study. To achieve the goal, this study implements Heuristic Gaussian Cloud Transformation (H-GCT) [16], which consists of two phases: (1) Heuristic Gaussian Transformation (H-GT) for data clustering and (2) Forward Cloud Generation (FCG) for enhancing uncertainty representation at the boundaries between adjacent scoring models. Prior to implementing this robust data-driven approach, statistical data on joint angles are extracted from the Construction Motion Data Library (CML) dataset. Subsequently, these developed scoring models are evaluated using Confusion degree (CD) values. This indicator effectively reflects the independence of scoring models and their accuracy in risk identification. Ultimately, a comparison is implemented with previous studies that adopted fuzzy logic to improve REBA, aiming to highlight the superiority of the data-driven H-GCT in developing scoring models.

2 Methodology

Figure 1 illustrates the workflow of the scoring model development process, which involves extracting statistical data from CML dataset and developing scoring models through H-GCT.

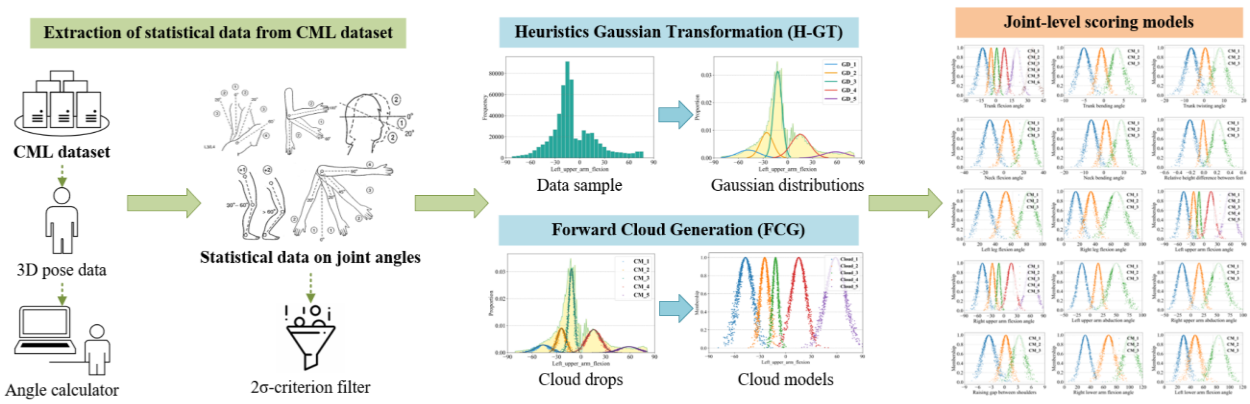


Figure 1. Workflow for the development of joint-level scoring models using H-GCT

2.1 Extracting statistical data from CML dataset

To obtain statistical data on joint angles of construction workers, the Construction Motion Data Library (CML) developed by Tian, Li [17] is selected. This dataset contains 4,333 samples of construction-related activities specifically curated for ergonomics analysis, covering five major types observed on construction sites, namely production activities, unsafe activities, awkward activities, common activities, and other activities. The dataset provides useful 3D pose data (20-joint system) for analysis.

In this study, based on REBA [3], 15 joint-level assessment modules are selected to cover five critical body segments: trunk, neck, legs, upper arms, and lower arms. Table 1 provides an overview of these modules and corresponding score distributions. Taking the Trunk Flexion module as an example, its assessment rules in REBA are as follows: an upright position (i.e., 0° flexion) is assigned a score of 1, a flexion or extension angle of 0-20° is assigned a score of 2, a flexion angle of 20°-60° or an extension angle greater than 20° is assigned a score of 3, and a flexion angle greater than 60° is assigned a score of 4. Following the progression of trunk flexion angles from negative to positive (with extension angles defined as negative), the corresponding scores change sequentially as 3, 2, 1, 2, 3, and 4, respectively (as illustrated in Table 1). Using the extracted 3D pose data, a vector-based calculator is utilized to obtain statistical data on joint angles for the 15 modules. Prior to developing the scoring models, the 2σ-criterion is applied, which sets the threshold at two standard deviations from the mean [18]. This criterion effectively eliminates potential outliers while preserving underlying data distributions.

2.2 Developing scoring models through H-GCT

Building upon the filtered statistical data on joint angles, the Heuristic Gaussian Cloud Transformation (H-GCT) is subsequently utilized to generate scoring models. Compared to other data-driven heuristic and clustering algorithms, such as Gaussian Mixture Model (GMM) [19] and K-Means [20], H-GCT effectively leverages prior knowledge from REBA to predefine the number of generated models while showcasing the capability to synthetically describe uncertainty [16]. The implementation of H-GCT follows two steps [21, 22]: Firstly, the H-GT generates a predefined number of clusters that align with joint-level assessment modules of REBA (i.e., the Gaussian distributions), based on the input data samples. Subsequently, the Forward Cloud Generation (FCG) develops cloud model to enhance uncertainty representation at boundaries between adjacent scoring models.

2.2.1 Data clustering by H-GT

Based on the score distributions of the assessment modules, the Heuristic Gaussian Transformation (H-GT) is selected to generate a predefined number of Gaussian Distributions (GDs) [19]. The H-GT algorithm leverages prior knowledge from REBA to determine the number of clusters, denoted as M, within each specific module. This allows a set of data samples to be partitioned into a superposition of M GDs. For a random variable x in the problem domain, which represents joint angles for each module, the frequency distribution function p(x) can be constructed. After the H-GT process, the mathematical expression for p(x) is given by formula (1) [16].

$$p(x) \rightarrow \sum_{i=1}^{M} (w_i G) \tag{1}$$

In formula (1):

$$G = \frac{1}{\sqrt{(2\pi)^d |Cov_i|}} e^{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)} \tag{2}$$

Among these parameters, w_i, μ_i, and Cov_i represent the amplitude, expectation, and covariance matrix of the i-th GD after transformation, respectively, with the w_i satisfying the condition $\sum_{i=1}^{M} w_i = 1$. Furthermore, d represents the dimension of the data sample while M is the predefined number of clusters.

Table 1 An overview of considered assessment modules

Joint-level assessment module	Score distribution
Trunk Flexion	3, 2, 1, 2, 3, 4
Trunk Bending	1, 0, 1
Trunk Twisting	1, 0, 1
Neck Flexion	2, 1, 2
Neck Adjustment	1, 0, 1
Legs Support	2, 1, 2
Legs Flexion (left)	0, 1, 2
Legs Flexion (right)	0, 1, 2
Upper Arms Flexion (left)	2, 1, 2, 3, 4
Upper Arms Flexion (right)	2, 1, 2, 3, 4
Upper Arms Abduction (left)	1, 0, 1
Upper Arms Abduction (right)	1, 0, 1
Gap between Shoulders	1, 0, 1
Lower Arms Flexion (left)	2, 1, 2
Lower Arms Flexion (right)	2, 1, 2

During the H-GT process, the Expectation Maximization (EM) algorithm is employed as an iterative optimization technique for parameter estimation in GDs with hidden variables [23]. It combines with Maximum Likelihood Estimation (MLE) and involves two main steps: the E-step for posterior probability calculation and the M-step for reassessment and optimization.

For the implementation, the EM algorithm is configured to iterate 100 times by default. The number of components, which corresponds to the generated GDs, is determined for each module based on the respective score distribution. Powered by the scikit-learn library and Python (version 3.9.12), the statistical data on joint angles for the 15 considered modules undergo transformation into 15 sets of GDs.

2.2.2 Cloud models generation by FCG

The H-GT process facilitates the transformation of continuous data samples into a superposition of multiple GDs. Each element within the generated GDs is associated with a membership degree determined by the probability values on each relevant GD (one-to-one correspondence). However, the absence of interpreting probable one-to-many correspondence at the boundaries between adjacent models introduces uncertainty. To address this, the Cloud Model (CM), functioning a cognitive model capable of synthetically describing the uncertainty, is employed [24]. Consequently, it optimizes the robustness of assessment.

During the FCG process, three numerical characteristics, namely Ex (expectation), En (entropy), and He (hyper entropy) are routinely employed to provide a comprehensive representation of a CM. Specifically, Ex represents the most representative data sample within a cluster, En quantifies the granularity scale of the cluster, and He portrays the uncertainty of the cluster granularity. As a result, a set of CMs can serve as the specific scoring models for a considered assessment module [25].

To determine the above Ex, En, and He before generation of CMs, the following steps are involved:

(i) For the k-th GD after H-GT, its mean and standard deviation are μ_k and σ_k, respectively.

(ii) The current standard deviation is considered as the maximum granularity parameter of the concept, while keeping the expectation constant to achieve equal scaling. Subsequently, the scaling ratios α_1 and α_2 of the k-th GD are computed to avoid overlap between adjacent clusters. These scaling ratios are determined using the following formulas (3) and (4) [16]:

$$\mu_{k-1} + 3\alpha_1\sigma_{k-1} = \mu_k - 3\alpha_1\sigma_k \tag{3}$$

$$\mu_k + 3\alpha_2\sigma_k = \mu_{k+1} - 3\alpha_2\sigma_{k+1} \tag{4}$$

Then, the variation range of standard deviation caused by unclear conceptual partition in the k-th GD is $[\alpha \times \sigma_k, \sigma_k]$, where $\alpha = \min(\alpha_1, \alpha_2)$.

(iii) According to the theory of Gaussian Cloud, that is, the standard deviation follows a GD, En is the expectation of standard deviation, and He is the standard deviation of the standard deviation [16]. The parameters and Confusion degree (CD) of the k-th CM can be determined as formulas (5) to (8) [16]:

$$Ex_k = \mu_k \tag{5}$$

$$En_k = (1+\alpha) \times \sigma_k/2 \tag{6}$$

$$He_k = (1-\alpha) \times \sigma_k/6 \tag{7}$$

$$CD_k = 3 \times He_k/En_k = (1-\alpha)/(1+\alpha) \tag{8}$$

Following the FCG, the 15 sets of GDs corresponding to the considered modules are transformed into 15 sets of CMs. These CMs serve as the scoring models for the assessment. Each CM consists of numerous cloud drops, which allow for the representation of uncertainty between adjacent models.

Table 2 Confusion degrees of all generated CMs

Assessment module	Confusion degrees (CDs)
Trunk Flexion	0.56, 0.56, 0.51, 0.45, 0.38, 0.36
Trunk Bending	0.43, 0.49, 0.49
Trunk Twisting	0.53, 0.53, 0.51
Neck Flexion	0.46, 0.46, 0.36
Neck Adjustment	0.47, 0.47, 0.46
Legs Support	0.45, 0.45, 0.38
Legs Flexion (left)	0.40, 0.40, 0.39
Legs Flexion (right)	0.50, 0.50, 0.39
Upper Arms Flexion (left)	0.47, 0.51, 0.51, 0.29, 0.29
Upper Arms Flexion (right)	0.48, 0.48, 0.46, 0.30, 0.28
Upper Arms Abduction (left)	0.31, 0.40, 0.40
Upper Arms Abduction (right)	0.33, 0.40, 0.40
Gap between Shoulders	0.46, 0.55, 0.55
Lower Arms Flexion (left)	0.59, 0.59, 0.40
Lower Arms Flexion (right)	0.31, 0.42, 0.42

3 Results and discussions

3.1 Developed joint-level scoring models

Through the H-GCT process, 15 sets of scoring models are developed for the 15 considered joint-level assessment modules in Table 1. As shown in Figure 2, these scoring models consist of multiple CMs (cloud models) that intuitively represent the correspondences between input joint angles and membership degrees of each risk category. The CMs synthetically describe the one-to-many uncertainty at the edges of adjacent scoring models, thereby optimizing the robustness of joint-level ergonomic assessment.

During the assessment process, the joint parameters for a specific module (e.g., joint angles) are inputted into the corresponding joint-level scoring model (Figure 2). The output of this process is a fuzzy set, which comprises a series of membership degrees. Each degree corresponds to an individual CM included in the scoring model. To calculate the joint-level ergonomic risk score, the Center of Area (CoA) method is employed for defuzzification, benefiting from its comprehensive consideration of membership information [11]. In the case of the Trunk Flexion module, assuming an input angle value of 30°, the resulting membership degrees from the six CMs are 2.81e-14, 6.91e-75, 5.82e-50, 3.33e-17, 1.48e-02, and 9.85e-01, respectively. According to Table 1, these CMs correspond to the score values of 3, 2, 1, 2, 3, and 4. By utilizing the CoA method for defuzzification, the risk score for this module is determined to be 3.99.

To evaluate the performance of the H-GCT, Confusion degree (CD) is utilized as a measure of the independence between generated CMs. This indicator exclusively quantifies the degree of overlap between adjacent CMs. It is worth noting that a more distinct division between CMs, characterized by minimal overlap, offers advantages in achieving more accurate assessment performance [16]. According to the computation results in Table 2, all generated CMs exhibit a significant level of independence. with all 52 CDs are below the threshold value of 0.64. This suggests the minimal of overlap or confusion in the core area of CMs [16].

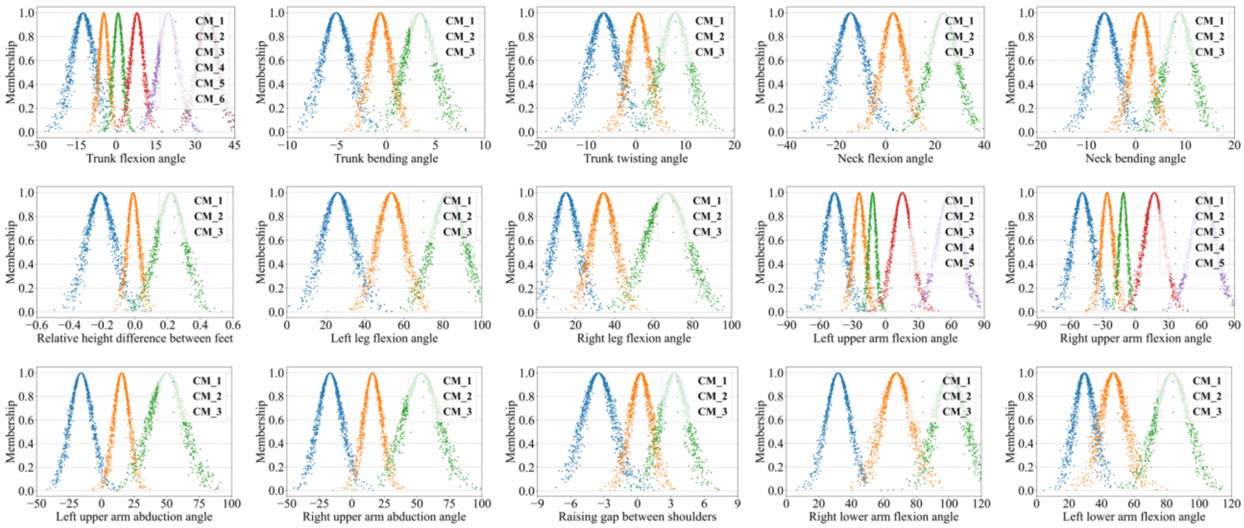
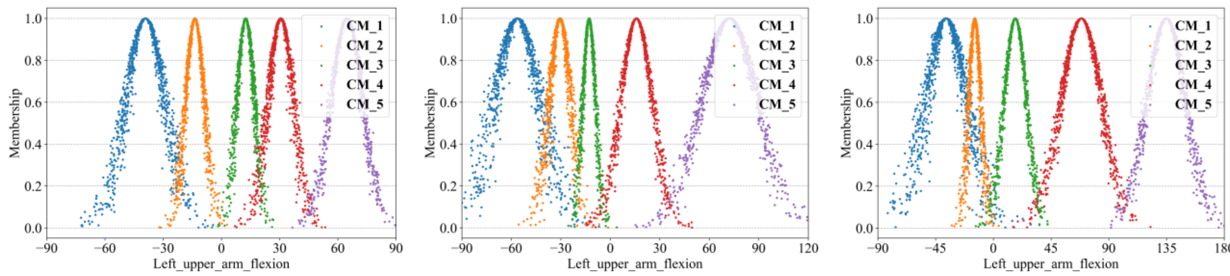


Figure 2. Developed 15 sets of joint-level scoring models



(b) by 2σ criterion-based data filtering

(b) by 3σ criterion-based data filtering

(c) no data filtering

Fig.3 Comparison of generated CMs for Upper arm flexion (left) under different data filtering criteria

3.2 Performance of H-GCT

This section focuses on two crucial parameters that exert substantial influence on the performance of H-GCT. In specific, the threshold criterion for data filtering and the number of iterations during H-GT are investigated.

Firstly, the performance of the 2σ-criterion is compared with that of the 3σ-criterion (resulting in less data being deleted) and no data filtering. The Upper Arm Flexion (left) assessment module's complexity is used as an example in Figure 3 to illustrate the generated CMs under these three criteria. It is evident that increasing the amount of deleted data leads to a reduction in overlaps between adjacent CMs, and the 2σ-criterion has generated CMs with the highest level of independence.

Secondly, the iteration process of H-GT is examined, specially focusing on the calculation of the likelihood estimation value to observe the EM (Expectation

Maximization) algorithm. Figure 4 reveals that H-GT for upper flexion angles data has undergone sufficient transformation as it approached the default 100^{th} iteration and beyond. This is evident from the nearly highest estimated value and the reduction of fluctuations (notable fluctuations observed from the 10^{th} to the 80^{th} iterations). Furthermore, the generated GDs (Gaussian Distributions) at the 80th, 90th, 100th, 110th, and 120th iterations are plotted to provide a detailed representation of the iterative progression towards the optimal state.

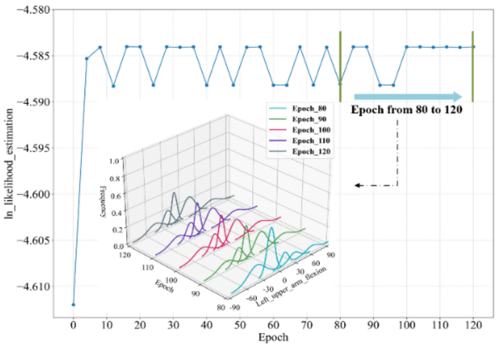


Figure 4. Iteration process of H-GT for statistical data on left upper arm flexion angles

3.3 Comparative analysis of scoring models with prior methods

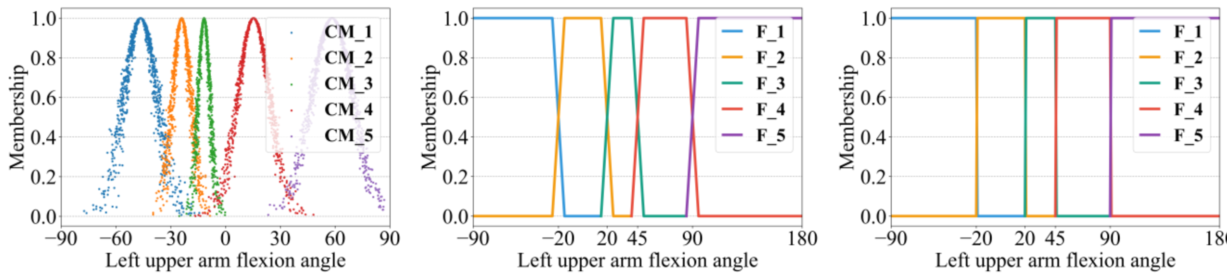
This section conducts a comprehensive comparison of the generated scoring models with previous methods. Prior explorations have addressed the issue of sharp transitions between risk categories in REBA by employing fuzzy logic [1, 11, 13, 26]. These efforts aim to mitigate the impact of instrument errors [6] and inevitable human perceptual biases [4] on assessment accuracy. To facilitate the comparison, the Upper Arm Flexion (left) and Trunk Twisting modules are selected as representative examples. Figure 5 and Figure 6 are presented to illustrate the comparison of cloud models (abbreviated as CM) and membership functions (abbreviated as F) involved. These two modules represent typical joint-level assessment modules of REBA, characterized by discrete boundaries and binary rules, respectively.

Firstly, notable differences can be observed in the input domains of generated cloud models and corresponding membership functions in REBA. This disparity primarily arises from the fact that REBA is developed based on the knowledge and experience of ergonomists [3], while the data-driven H-GCT generates scoring models based on extensive pose data from construction workers. Although the utilization of fuzzy logic by Wang, Han [11] effectively improve the traditional REBA, its focus remains limited to membership functions' shape and threshold settings, without fundamental altering the input domains of these functions.

Notably, the function shapes exhibit differences between the scoring models and other membership functions. Previous studies introduced fuzzy logic to improve REBA involving predetermined shapes such as trapezoidal and triangular functions [11, 26]. In contrast, in this study, the function shape is uniformly initialized as Gaussian distribution and iteratively optimize during the H-GCT process [16]. The incorporation of fuzzy logic effectively mitigates sharp transitions between risk categories, as evidenced by Figure 5(b). However, within each membership function improved by fuzzy logic, there are still notable instances where changes in angle do not correspond to changes in the assigned risk category, indicating certain unrealistic aspects.

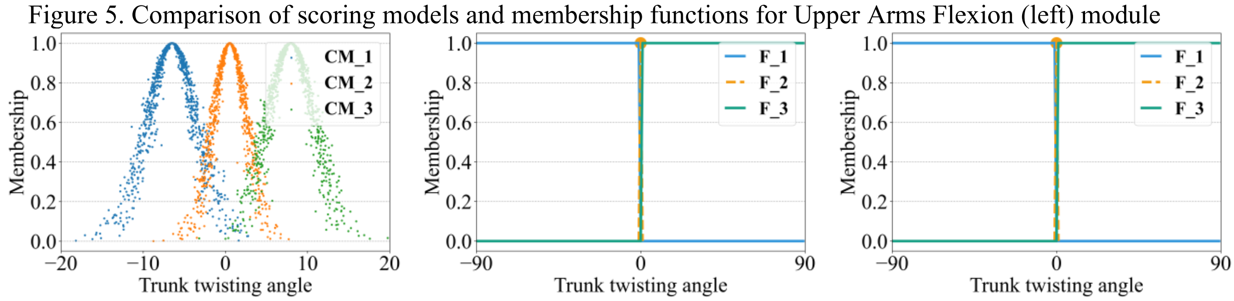
Moreover, the threshold settings for fuzzy logic impact a direct influence the degree of overlap between adjacent functions, thereby affecting the distribution of membership functions. Previous studies typically relied on predetermined threshold values, such as 5° threshold adopted by Wang, Han [11]. On the contrary, the data-driven H-GCT approach employs an iterative optimization process to dynamically adjust the thresholds (i.e., overlap area) between adjacent cloud models. This dynamic adjustment process serves to minimize the Confusion degrees (CD) and, consequently, enhance the accuracy of assessment.

Ultimately, it is worth noting that previous studies failed to effectively improve the binary rule-based assessment modules of traditional REBA [1, 11, 13, 26]. These modules exhibit remarkable susceptibility to instrument errors and human perceptual biases, given their utilization of a limited and unrealistic input domain for certain membership functions. For instance, the practice of "assigning a risk score of 0 when the trunk twisting angle is 0°" fails to accurately reflect the true ergonomic risk. To overcome this limitation, the H-GCT generates scoring models that incorporate a reasonably expanded input domain for these functions, as illustrated in Figure 6(a).



(a) scoring models generated by H-GCT (b) membership functions improved by Fuzzy logic (c) membership functions determined by REBA

Figure 5. Comparison of scoring models and membership functions for Upper Arms Flexion (left) module



(a) scoring models generated by H-GCT (b) membership functions improved by Fuzzy logic (*no improvements) (c) membership functions determined by REBA

Figure 6. Comparison of scoring models and membership functions for Trunk Twisting module

4 Conclusion

This study primarily contributes to the existing body of knowledge concerning the occupational health and safety management on construction sites. It accomplishes this by developing joint-level scoring models tailored to whole-body ergonomic assessment of construction workers. Specifically, a robust and heuristic data-driven approach named H-GCT is employed, leveraging statistical data on joint angles extracted from a comprehensive CML dataset.

The results demonstrate that the CMs involved in generated scoring models exhibit a substantial level of independence, as evidenced by all Confusion degrees remaining below the threshold value of 0.64. This high level of independence contributes to the accurate identification of ergonomic risk. Furthermore, a comparison is conducted with previous studies that employed fuzzy logic to improve REBA. This process highlights the superiority of the data-driven H-GCT in developing scoring models.

In terms of practical use, the output of these scoring models can be collaborated with fuzzy inference to achieve both accurate and continuous whole-body risk scores, enhancing the applicability. Moreover, for future studies, it is recommended to improve the work by expanding pose data, enriching assessment modules, and refining the data-driven approach.

5 Acknowledgement

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