An sEMG-Enhanced Fuzzy REBA for Forearm Risk Assessment

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Abstract –

Accurate ergonomic risk assessment is critical for occupational safety in construction. However, the widely used observation-based tool Rapid Entire Body Assessment (REBA) may suffer from low sensitivity arising from stepwise score assignment and limited accuracy due to joint angle categories defined without the support of muscle activity data.

To address this limitation, this study proposes a surface electromyography-Enhanced Fuzzy REBA (SEF REBA) that augments REBA with probabilistic modeling and fuzzy inference. Surface electromyography (sEMG) derived muscle activation is integrated with joint angles to define data-driven boundaries.

Using a manual material handling task dataset with synchronized joint kinematics and sEMG, this study focuses on forearm (elbow) assessment and proceeds in two stages: (1) Clustering posture instances in a joint angle-sEMG feature space via Heuristic Gaussian Cloud Transformation to improve range setting reliability. (2) Designing a fuzzy inference mechanism using joint angle dimension distribution functions to achieve gradual transitions of risk score.

The joint angle–sEMG clustering reveals biomechanical posture patterns not captured by joint angle alone. SEF REBA leverages these clusters to generate fuzzy memberships and continuous elbow risk scores while remaining compatible with original REBA framework. Compared with original and fuzzy REBA, SEF REBA shows continuous risk score changes across the full motion range, avoiding abrupt score transitions and providing a physiologically meaningful risk response.

This framework upgrades REBA with biomechanically informed scoring rules and fuzzy reasoning, enhancing both sensitivity and physiological relevance while retaining interpretability. Future work will extend the approach to additional joints and refine muscle-contribution weights during clustering.

Keywords: Ergonomics, Rapid Entire Body Assessment, Fuzzy logic, Gaussian mixture model, Surface Electromyography.

1 Introduction

Work-related musculoskeletal disorders (WMSDs) constitute one of the most significant occupational health challenges worldwide, particularly in physically demanding industries like construction [1]. WMSDs refer to a broad class of injuries and disorders affecting muscles, tendons, and associated soft tissues, which are strongly linked to repetitive tasks, awkward postures, and excessive biomechanical loading [2]. In Canada, WMSDs represent the leading cause of work-related injury claims, accounting for roughly 30-40% of accepted claims in provincial workers' compensation systems [3]. Beyond adverse effects on workers' health, WMSDs impose considerable economic and social burdens through productivity losses and compensation costs [4]. These persistent and severe impacts highlight the critical need for effective ergonomic risk assessment methods to identify hazardous work conditions and support proactive safety interventions in construction activities.

Observational approaches are widely adopted for ergonomic risk assessment because they offer a favorable trade-off among feasibility, cost-effectiveness, and actionable interpretability [5]. These methods evaluate working postures and physical workload through on-site observations or video-based analysis, enabling rapid identification of potential hazards with minimal cost and limited disruption to production processes [5-6]. Representative observational tools include the Rapid Upper Limb Assessment (RULA), the Rapid Entire Body Assessment (REBA), the NIOSH lifting equation, and the revised Strain Index (SI) [7-10].

REBA is one of the most widely used observation-based ergonomic risk assessment methods due to its simplicity, low cost, and broad applicability across diverse tasks [11]. Recent studies have further proposed automated REBA pipelines using computer vision–based pose estimation, marker-based motion capture, and wearable inertial measurement unit (IMU) sensors, primarily to improve the accuracy, objectivity, and efficiency of obtaining joint kinematics [12-13]. However, even with more precise kinematic inputs, two intrinsic limitations of REBA still remain. First, REBA exhibits low sensitivity due to its rigid boundary scoring setting, which produces abrupt transitions and fails to reflect incremental postural changes in a single risk range [14-15]. Second, REBA may not accurately represent ergonomic risks. Its joint angle dominant category assignment lacks muscle data support, which does not account for muscle fatigue [16].

Recently, some advancements have been achieved in these issues. Multiple studies have incorporated fuzzy logic into REBA to smooth score transition and better capture gradual risk changes in a single risk range [17-19]. Nevertheless, the definition of membership functions and rules in fuzzy logic-related methods often depends on subjective judgement, which hinders objectivity and generalization across tasks and populations [18]. In parallel, to improve limited accuracy, data-driven refinements have been proposed to redefine joint angle ranges using motion datasets, which can enhance risk identification and provide more reliable boundary setting [14]. However, these approaches are frequently kinematics-only, which lacks direct physiological evidence to support fatigue-related risk interpretation [20]. Meanwhile, several studies leverage surface electromyography (sEMG) data to classify ergonomic risks, but such EMG-driven outputs are commonly reported as coarse labels (e.g., low/high risk) rather than being quantitatively embedded into REBA scoring system [21], leaving the integration between muscle-informed evidence and REBA unresolved.

Collectively, these gaps motivate the need for a principled ergonomic risk assessment framework that simultaneously reduces subjectivity in fuzzy membership construction and quantitatively incorporates muscle data information into REBA's framework. To address this need, this study proposes an sEMG-Enhanced Fuzzy REBA (SEF REBA) framework, with a specific focus on elbow joint, that integrates joint kinematics and sEMG in a data-driven interpretable manner. The proposed method consists of two stages: (1) developing a revised forearm (elbow) scoring model based on Heuristic Gaussian Cloud Transformation (HGCT) to cluster posture instances in a joint angle-sEMG feature space, where prior knowledge derived from REBA risk score category setting is embedded. (2) designing a fuzzy inference mechanism by constructing membership functions from joint angle marginal distributions of HGCT, enabling smooth and continuous risk transitions. By leveraging joint angle-sEMG data in a data-driven fashion, this study enables proactive identification of implicit biomechanical knowledge that is not readily observable from posture alone, thereby contributing to a more physiologically meaningful ergonomic risk assessment. The proposed method provides a viable way for enhancing traditional observational tools while maintaining their practical interpretability and compatibility with established ergonomic standards.

2 Methodology

The overview workflow is shown in Figure 1, which includes data acquisition and model development, and then illustrates how to assign this adjustment for the original REBA.

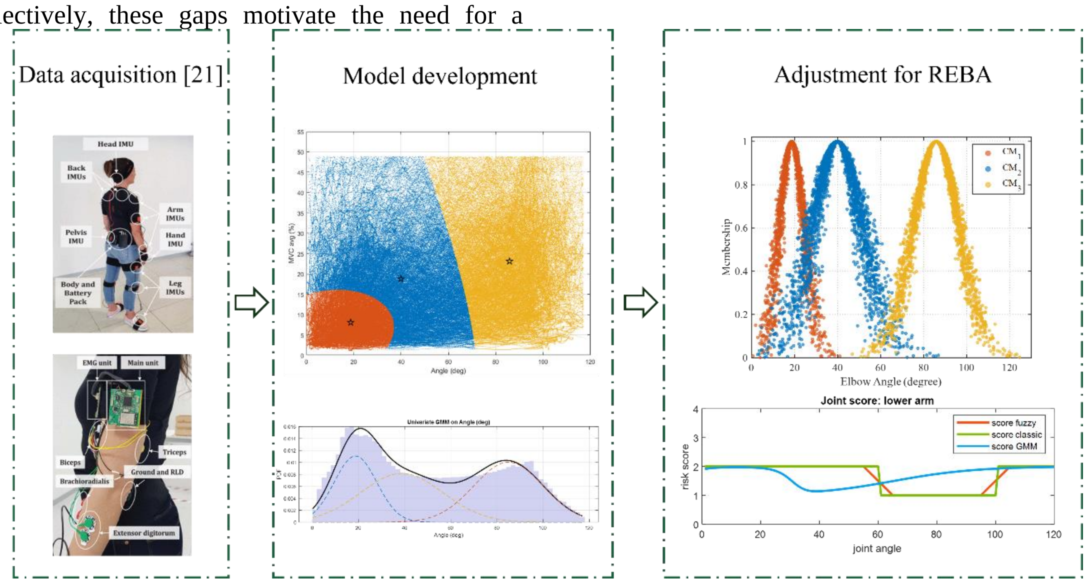


Figure 1. Workflow for developing SEF REBA

In the original REBA, the elbow (lower arm) risk is assessed using discrete flexion angle ranges, with each range assigned a predefined risk score: a flexion angle of 0°-60° is assigned a score of 2, a flexion angle of 60°-100° is assigned a score of 1, and a flexion angle above 100° is assigned a score of 2. This rule is primarily developed in task contexts more consistent with manufacturing and assembly work, where upper-limb postures are often performed under relatively fixed workstation conditions [8]. In contrast, manual material handling (MMH) and construction-related tasks commonly involve unsupported load handling, in which elbow flexion directly contributes to load transfer and upper-limb biomechanical demand. Under these conditions, the original elbow score setting in REBA may not adequately reflect the actual ergonomic burden. Because this mismatch is particularly evident in the elbow module, the present study focuses on elbow risk assessment. This joint-level focus is intended as a first step, and future work may extend to other joints.

Following this overview, Section 2.1 describes the data acquisition and preprocessing procedures. Section 2.2 then presents the development of the data-driven elbow scoring model based on HGCT.

2.1 Data acquisition and preprocessing

The data used in this study are obtained from a publicly available, fully labeled dataset of motion and muscular activities during MMH tasks [22]. The dataset is collected in controlled laboratory settings and includes synchronized full-body kinematics from 17 IMUs and upper limbs sEMG data from 4 muscles (biceps, triceps, brachioradialis, and extensor digitorum). 14 healthy subjects (30.57±4.57 years old) participated in the experiments [22].

In this study, isokinetic activity subset of the dataset is chosen for model building. During these trials, subjects lift and lower the dumbbell with an elbow flexion-extension, while maintaining the upper arm aligned with the torso (shoulder abduction and flexion constrained at 0°). Elbow angles are expressed in flexion angle with positive values; 0° means full extension. Load-handling conditions are varied by combining two load weights (2 and 4 kg) with multiple angular velocities (60°/s, 90°/s, and 120°/s).

For subsequent elbow scoring model development, the sEMG representation is defined as the average RMS of biceps brachii, triceps brachii, and brachioradialis, because these muscles are directly related to elbow flexion. Extensor digitorum is excluded from this averaged feature because it mainly contributes to finger extension. The resulting averaged RMS provides an overall muscle activation description for integration with joint angle data.

Standard preprocessing procedures are applied to the raw sEMG recordings to derive RMS features. Briefly, the signals are baseline-corrected, band-pass filtered (20–450 Hz, 4th-order Butterworth), full-wave rectified, and low-pass filtered at 6 Hz to obtain the linear envelope. Then, the sEMG signals are normalized to maximum voluntary contraction (MVC) and are expressed as %MVC. Following Equation (1), RMS features are then computed using a sliding-window approach with a window length of 200 ms and a step size of 50 ms [23]. The resulting RMS features are temporally aligned with the corresponding elbow joint angle data and used as inputs for model development.

$$RMS = \sqrt{\frac{\int_{-\frac{T}{2}}^{\frac{T}{2}} EMG^2(t)dt}{T}} \tag{1}$$

2.2 Development of SEF REBA elbow scoring model using HGCT

2.2.1 Heuristic Gaussian modeling with REBA prior knowledge

This study adopts joint angle and sEMG as a joint calibration space, in which their distribution is modeled and clustered to identify latent elbow risk patterns and to calibrate the angle-based risk states in the REBA elbow score setting. HGCT framework is adopted as the modeling paradigm to bridge statistical learning and ergonomic risk representation. HGCT builds upon the Gaussian Mixture Model (GMM) while enabling subsequent transformation toward uncertainty awareness and continuous risk descriptions. Under this framework, GMM serves as the probabilistic foundation for modeling joint angle and sEMG observations with REBA prior knowledge, from which the underlying statistical structures are learned and subsequently transformed into interpretable scoring representations. Specifically, each observation is represented in a joint angle-sEMG feature space as Equation (2)

$$x_i = [\,\theta_i, e_i\,] \tag{2}$$

Where θ_i denotes the elbow angle and e_i denotes the corresponding sEMG activation level quantified by RMS feature. The probability density function of x is modeled using GMM, expressed as Equation (3).

$$p(x) = \sum_{k=1}^{K} \pi_k\, \mathcal{N}(\,x \mid \mu_k, \Sigma_k\,) \tag{3}$$

Where K is the number of mixture components, π_k is the prior weight of the k-th component, and μ_k and Σ_k are its mean vector and covariance matrix, respectively. Each Gaussian component captures a posture-muscle load pattern in the joint angle-sEMG space. To ensure structural consistency with REBA framework, the number of Gaussian components K is assigned to three, corresponding to the three elbow angle ranges defined in the original REBA. The parameters of the GMM are estimated using the Expectation–Maximization (EM) algorithm by maximizing the log-likelihood of the observed joint angle–sEMG data.

2.2.2 Gaussian cloud model generation

Although the GMM is built in the joint angle–EMG space, the subsequent risk representation is formulated exclusively in the elbow angle domain to preserve compatibility with the original REBA. In this study, joint angle–EMG modeling serves as a calibration stage, whereas angle-based representation constitutes the final risk assessment stage. Therefore, the transformation from Gaussian components to cloud models is performed after projecting the learned joint distributions onto the elbow angle domain.

For each Gaussian component k, The marginal distribution with respect to elbow angle θ is obtained by integrating out the sEMG dimension. Given the properties of multivariate Gaussian distributions, the marginalization yields a univariate Gaussian distribution in the angle dimension, expressed as Equation (4).

$$p_k(\theta) = \mathcal{N}\left(\theta \mid \mu_{\theta,k}, \sigma_{\theta,k}^2\right) \tag{4}$$

Where $\mu_{\theta,k}$ and $\sigma_{\theta,k}^2$ are the mean and variance of the elbow angle extracted from the corresponding entries of μ_k, and Σ_k. It is important to note that this projection does not discard the influence of muscle activation. Instead, sEMG information has already shaped the location, dispersion, and overlap of each Gaussian component during the modeling and clustering stage. As a result, the angle domain Gaussian distributions implicitly encode biomechanical variability learned from the joint elbow angle–sEMG space.

Next, each angle-domain Gaussian component is transformed into a cloud model, which enables the explicit modeling of ambiguous boundaries between adjacent elbow risk states (risk scores for each state are 2, 1, 2). A scaling factor α is introduced to account for the ambiguity between neighboring angle categories. Specifically, for the k-th component, the following boundary consistency conditions are considered:

$$\mu_{\theta,k-1} + 3\alpha_1\sigma_{\theta,k-1} = \mu_{\theta,k} - 3\alpha_1\sigma_{\theta,k} \tag{5}$$

$$\mu_{\theta,k} + 3\alpha_2\sigma_{\theta,k} = \mu_{\theta,k+1} - 3\alpha_2\sigma_{\theta,k+1} \tag{6}$$

From which α_1 and α_2 are obtained. The final scaling factor is determined as:

$$\alpha = \min(\alpha_1, \alpha_2) \tag{7}$$

Based on Gaussian cloud theory, the parameters of the cloud model corresponding to the k-th Gaussian component are then defined as expectation (Ex_k), entropy (En_k), and hyper-entropy (He_k). They are calculated as:

$$Ex_k = \mu_{\theta,k} \tag{8}$$

$$En_k = \frac{(1+\alpha)\sigma_{\theta,k}}{2} \tag{9}$$

$$He_k = \frac{(1-\alpha)\sigma_{\theta,k}}{6} \tag{10}$$

For the k-th cloud model, each cloud drop is produced using the forward cloud generator. Specifically, an entropy realization En_k' is first sampled from a normal distribution $\mathcal{N}(En_k, He_k^2)$, and an angle value x_k is then generated from $\mathcal{N}\left(Ex_k, En_k'^2\right)$. The membership degree of the generated cloud drop is calculated as:

$$\mu_k = \exp\left[\frac{-(x_k - Ex_k)^2}{2En_k'^2}\right] \tag{11}$$

Repeating this process could yield a set of cloud drops (x_k, μ_k) that represent the spread, overlap, and uncertainty of the corresponding risk state in the angle domain. For interior components, the scaling factor α is determined using the two-sided neighboring constraints in Equations (5) and (6), whereas for the first and last components, only the right and left neighboring constraint is used.

2.2.3 Derivation of REBA-compatible elbow scoring model

For a given elbow angle, the Gaussian cloud model assigns fuzzy membership degrees to each joint category by equation (11). These membership degrees are then defuzzified using the center-of-area method to obtain a single elbow risk score, where each risk state contributes according to its membership degree and the corresponding REBA elbow score. This process yields a crisp and continuous elbow risk score, enabling smooth transitions across adjacent angle ranges and alleviating the rigid boundary effects of the original REBA. The resulting elbow scoring model operates exclusively on elbow joint angle as input and can be directly embedded into the original REBA without modifying its overall framework.

3 Results and discussion

3.1 Elbow Angle–sEMG Clustering Results

Figure 2 presents the clustering results obtained using a GMM with REBA prior knowledge, constructed in the joint feature space of elbow flexion angle and average RMS. Three Gaussian components are identified, corresponding to the three elbow risk categories defined in the original REBA scheme, each representing a distinct posture–muscle activation pattern in a probabilistic sense. The left cluster is characterized by small elbow flexion angles and low average muscle activation levels. The middle cluster spans moderate elbow flexion angles and is associated with increased and more dispersed muscle activation. The right cluster corresponds to large elbow flexion angles accompanied by consistently elevated muscle activation levels. The star markers denote the centroid of each cluster, representing the mean elbow angle and the mean average muscle activation. Notably, the angular coverage of the clusters does not strictly coincide with the angle ranges of each risk category defined in the original REBA elbow joint. The middle and right clusters span angle ranges that partially overlap multiple REBA risk categories, whereas the left cluster is confined to a comparatively narrower angle range.

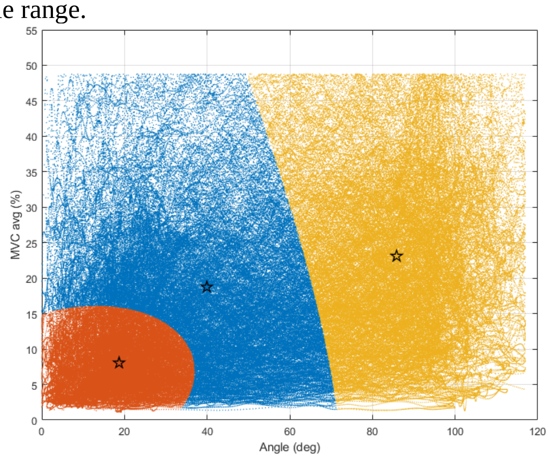


Figure 2. Elbow Angle–sEMG Clustering Results

The sEMG data influences the formation of these clusters during model development by acting as a physiological constraint. In the original REBA framework, where only elbow joint angle is considered, postures with similar kinematic configurations are typically grouped together based on expert-derived angle ranges. In the proposed approach, the GMM is required to account for variations in muscular loading among postures with comparable elbow angles by incorporating sEMG information. This constrained learning process further results in a calibration of the angle-based risk representation. Because sample assignment to each Gaussian component is jointly influenced by elbow angle and muscle activation, the marginal angle distributions of individual clusters are reshaped accordingly. As a result, the angle ranges of each cluster differ from the original REBA. In this way, the integration of sEMG data prevents the clustering process from being driven solely by joint angle and promotes a biomechanically informed separation of elbow angle–risk states.

Although the clustering results demonstrate that sEMG plays a critical role in shaping the underlying risk categories, the final fuzzy inference relies solely on elbow angle as input. This design represents a deliberate balance between biomechanical fidelity and practical applicability within the original REBA framework. Muscle activation is incorporated to constrain the learning stage and reduce bias in defining angle-based risk representations, rather than to increase the dimensionality of the inference stage.

From a mathematical perspective, the GMM learns a joint probability distribution over elbow angle and muscle activation for each latent risk state. By marginalizing over the sEMG dimension, the resulting angle distributions are directly interpreted as fuzzy membership functions, thereby embedding the influence of muscle activation into the shape and location of the angle-based memberships, even though sEMG is not explicitly used during inference. Importantly, the fact that a given elbow angle may correspond to multiple clusters in the joint elbow angle-sEMG space does not constitute a contradiction. Instead, it reflects intrinsic biomechanical variability that cannot be resolved by joint angle alone. Fuzzy membership functions provide a natural mechanism to represent this ambiguity, allowing an angle to partially belong to multiple angle categories with different degrees of membership. In this way, the uncertainty revealed by sEMG is preserved in the angle dimension representation rather than ignored.

From an application perspective, REBA's primary advantage lies in its rapid, posture-based assessment without the need for specialized instrumentation. Introducing sEMG as a required input would fundamentally alter this usage paradigm and increase implementation complexity. Accordingly, the proposed approach recalibrates the angle–risk relationship using sEMG as an offline physiological constraint, while preserving the operational simplicity and compatibility of the original REBA framework.

3.2 Cloud Model–Based Fuzzy Inference for SEF REBA Scoring

Figure 3 illustrates the three resulting cloud models (CMs) in the angle dimension (2500 cloud drops for each CM). Each cloud model occupies a distinct yet partially overlapping angle range, with cloud drops distributed around a well-defined central region. The horizontal spread of the cloud drops reflects the uncertainty of angle membership for each risk state, while the vertical dispersion represents the gradual transition of membership degrees across the angle continuum. The overlap among adjacent cloud models visually highlights the absence of rigid boundaries between risk states and provides an intuitive representation of smooth risk transitions.

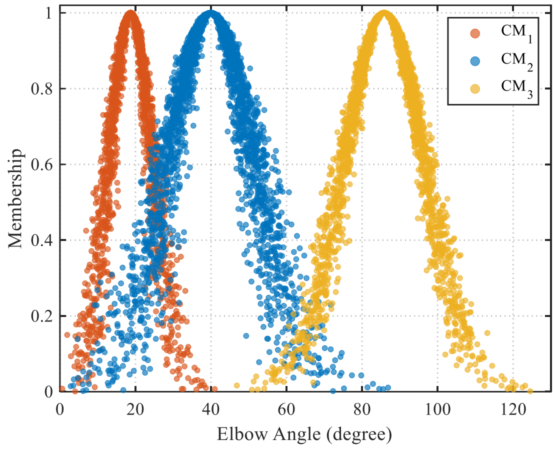


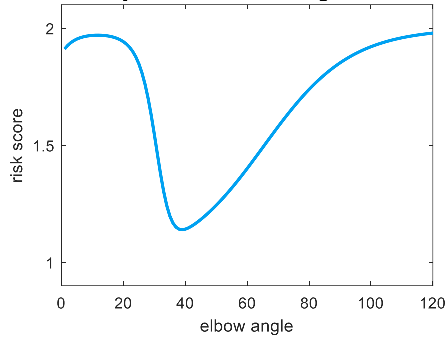
Figure 3. CMs of the elbow joint

To ensure compatibility with the original REBA framework, each cloud model is explicitly mapped to a predefined elbow risk score according to the original REBA elbow joint setting: a flexion angle of 0°-60° is assigned a score of 2, a flexion angle of 60°-100° is assigned a score of 1, and a flexion angle above 100° is assigned a score of 2. Following this definition, the three cloud models shown in Figure 3 are mapped to REBA risk scores of 2, 1, and 2 from left to right, according to their dominant angle regions.

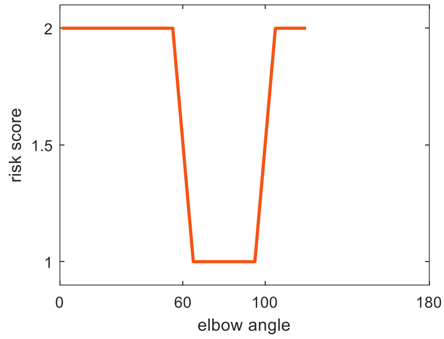
A representative elbow flexion angle of 30° is selected as a worked example to illustrate how the proposed SEF REBA framework operates in practice. For this input angle, fuzzy membership degrees are evaluated with respect to the three cloud models shown in Fig. 3. Specifically, the computed membership degrees are 0.25, 0.22, and 0.01 for the left, middle, and right cloud models, respectively. Following the computation of membership degrees, defuzzification is performed using the center-of-area (CoA) method in conjunction with the corresponding REBA risk scores assigned to the three cloud models (2, 1, and 2). By aggregating the fuzzy memberships with the predefined REBA scores, the proposed SEF REBA framework yields a continuous elbow risk score of 1.54 for the 30° posture, falling within the interval between 1 and 2 rather than being restricted to the discrete integer scores (1 or 2) of the original REBA.

3.3 Comparative Sensitivity Analysis of Original, Fuzzy, and SEF REBA

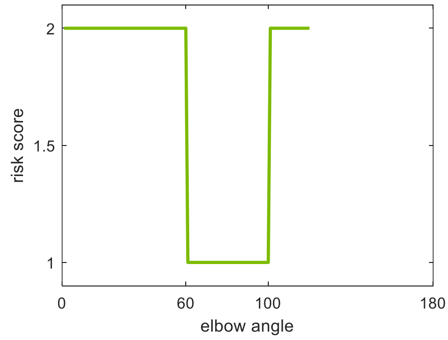
Figure 4 compares the elbow risk scores produced by the SEF REBA, Fuzzy REBA, and Original REBA as a function of elbow flexion angle. The original REBA (Figure 4 (c)) exhibits a strictly stepwise risk–angle relationship, indicating zero responsiveness to angle changes within each category. For fuzzy REBA (Figure 4 (b)) proposed by Wang et al., it reduces abrupt score jumps by introducing gradual transitions at category boundaries, but the risk curves remain piecewise flat, with sensitivity primarily localized near the boundaries (60° and 100°). In contrast, SEF REBA (Figure 4 (a)) yields a fully continuous risk score curve, with risk scores varying smoothly across a wide range of elbow angles. This behavior reflects a transition from sensitivity that is localized around predefined boundaries to a more distributed sensitivity over a wider range of motion.



(a) Risk score of SEF REBA



(b) Risk score of Fuzzy REBA



(c) Risk score of Original REBA

Figure 4. Risk scoring settings of SEF, fuzzy, and original REBA for the elbow joint

To further elucidate how risk scores respond to continuous posture variations, sensitivity value is characterized using the first-order derivative of the risk score with respect to elbow angle. Specifically, the magnitude of the derivative is used to quantify the instantaneous responsiveness of each REBA to changes in elbow angle:

$$S(\theta) = \left| \frac{dR(\theta)}{d\theta} \right| \tag{12}$$

$R(\theta)$ denotes the risk score as a function of elbow flexion angle θ. A sensitivity threshold ε is introduced to distinguish meaningful risk response from negligible variations. Because the original REBA exhibits zero sensitivity within each angle category, a small threshold value is sufficient to distinguish meaningful responses from numerical fluctuations. Accordingly, ε is set to 0.01 score/degree.

Figure 5 presents the distribution of $S(\theta)$ over the full elbow angle range for the SEF REBA, fuzzy REBA, and original REBA. The right panel of Figure 5 provides a rescaled view of the shaded boundary regions (55°–65° and 95°–105°) from the left panel, with an expanded y-axis (0–1) to highlight local variations near the original REBA boundaries. For the original REBA, nonzero sensitivity value is observed only at the predefined boundaries (60° and 100°), where abrupt score transitions result in extremely sharp derivative peaks. Outside these boundary points, $S(\theta)$ remains identically zero, indicating that posture variations within each angle category do not influence the assessed risk. This behavior confirms that the sensitivity of the discrete REBA is entirely confined to boundary locations. Fuzzy REBA mitigates these discontinuities by introducing smooth transitions through subjective fuzzy membership functions. As a result, finite sensitivity regions emerge around the original REBA boundaries, replacing the singular peaks with bounded responses. However, the derivative remains zero across most of the angular domain, demonstrating that sensitivity is still predominantly localized in narrow boundary regions, while interior angle ranges remain largely insensitive to posture changes. In contrast, SEF REBA exhibits nonzero sensitivity values over a substantially broader range of elbow angles, with smoothly varying derivative magnitudes and without pronounced spikes. This distributed sensitivity indicates that the continuous score retains intermediate risk variation that is suppressed by discrete category-based scoring. As a result, risk can be represented more faithfully across the motion range, and the resulting risk output is more suitable for automated continuous monitoring, including trend tracking and peak identification within dynamic motions.

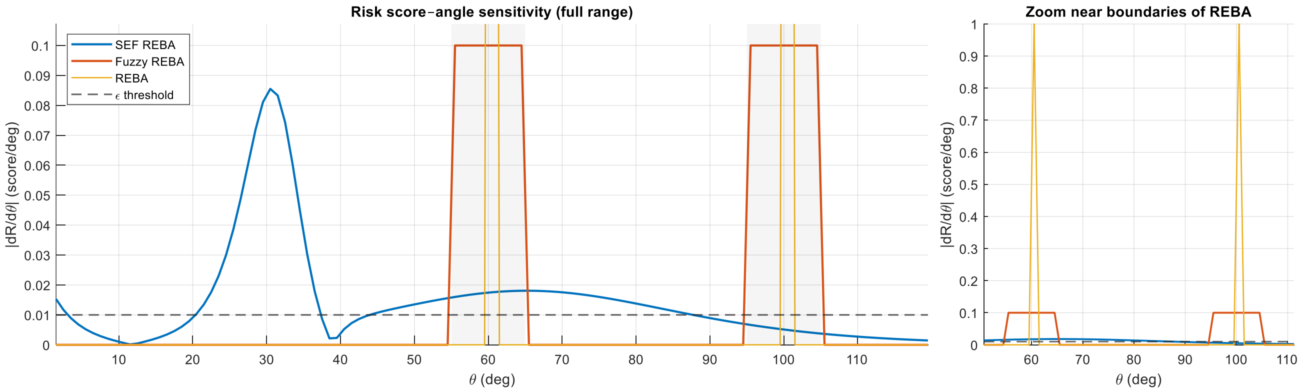


Figure 5. Derivative-based sensitivity of SEF REBA, *fuzzy REBA, and original REBA*

4 Conclusion

This study proposes a surface electromyography-Enhanced Fuzzy REBA (SEF REBA) framework to address the low sensitivity and limited accuracy issues of the conventional REBA method, with a focus on elbow joint risk assessment in manual material handling tasks. By integrating joint angle and sEMG data within HGCT framework, the proposed approach enhances the reliability of joint angle–risk mapping while preserving the operational simplicity and interpretability of the original REBA system.

The results demonstrate that incorporating sEMG information at the model-building stage leads to meaningful adjustments of the elbow angle–risk relationship. Compared with original and fuzzy REBA methods, SEF REBA exhibits nonzero sensitivity across the full motion range and avoids abrupt score transitions near angle category boundaries. The resulting risk response is smoother, more stable, and more consistent with underlying biomechanical loading conditions, providing a principled interpretation of biomechanical variability that cannot be resolved by joint angle alone.

From a practical perspective, the proposed framework offers a viable pathway for upgrading observational ergonomic assessment tools using physiological evidence, while maintaining their ease of deployment. SEF REBA can be readily embedded into existing REBA-based assessment pipelines, including video-based or sensor-based posture extraction systems, without increasing input dimensionality or instrumentation requirements in field applications. This makes the method particularly suitable for construction and industrial settings, where rapid assessment, interpretability, and low implementation cost are essential. Future work will build the model with more realistic construction scenarios, extend the approach to additional joints, refine muscle-contribution weights during clustering, and further validate scoring accuracy through experiments.

References

[1] Seo, JoonOh, and SangHyun Lee. Automated postural ergonomic risk assessment using vision-based posture classification. *Automation in Construction*, 128 : 103725, 2021.

[2] Punnett, Laura, and David H. Wegman. Work-related musculoskeletal disorders: the epidemiologic evidence and the debate. *Journal of electromyography and kinesiology*, 14.1: 13-23, 2004.

[3] WorkSafeBC. Musculoskeletal injuries (MSIs) and time-loss claims in British Columbia. On-line: https://www.worksafebc.com, Accessed:01/09/2026.

[4] Chen, Ningjing, and Janet Yuen Ha Wong. Health and economic outcomes associated with musculoskeletal disorders attributable to high body mass index in 192 countries and territories in 2019. *JAMA Network Open*, 6.1: e2250674-e2250674,2023.

[5] Graben, Preston Riley, et al. Reliability analysis of observation-based exposure assessment tools for the upper extremities. *International Journal of Environmental Research and Public Health*, 19.17: 10595, 2022.

[6] Iyer, Hari, et al. A scoping review on emerging technologies and automation of musculoskeletal ergonomic assessments. *Ergonomics*: 1-26, 2025.

[7] McAtamney, Lynn, and E. Nigel Corlett. RULA: a survey method for the investigation of work-related upper limb disorders. *Applied ergonomics*, 24.2: 91-99, 1993.

[8] Hignett, Sue, and Lynn McAtamney. Rapid entire body assessment (REBA). *Applied ergonomics*, 31.2: 201-205, 2000.

[9] Waters, Thomas R. Revised NIOSH equation for the design and evaluation of manual lifting tasks. *Ergonomics*, 36.7: 749-776, 1993.

[10] Garg, Arun, J. Steven Moore. The Revised Strain Index: an improved upper extremity exposure assessment model. *Ergonomics*, 60.7: 912-922, 2017.

[11] Hita-Gutiérrez, Manuel. An overview of REBA method applications in the world. *International journal of environmental research and public health*, 17.8: 2635, 2020.

[12] Fan, Chao, Qipei Mei, and Xinming Li. 3D pose estimation dataset and deep learning-based ergonomic risk assessment in construction. *Automation in Construction*, 164: 105452, 2024.

[13] Vox, Jan P. An evaluation of motion trackers with virtual reality sensor technology in comparison to a marker-based motion capture system based on joint angles for ergonomic risk assessment. *Sensors*, 21.9: 3145, 2021.

[14] Li, Zirui, et al. Data-driven ergonomic assessment of construction workers. *Automation in Construction*, 165: 105561, 2024.

[15] J. Zhu, X. Li. Adjustments for improved upper arm adjustment factor in REBA and RULA methods based on postural sway analysis. In *CSCE Construction Specialty Conference and ASCE Construction Research Congress (CRC)*, Canada, 2025.

[16] David, Geoffrey C. Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. *Occupational medicine*, 55.3: 190-199, 2005.

[17] Wang, Jingwen, SangHyeok Han, and Xinming Li. 3D fuzzy ergonomic analysis for rapid workplace design and modification in construction. *Automation in construction*, 123: 103521, 2021.

[18] Kavus, Bahar Yalcin, and Alev Taskin. A comparative neural networks and neuro-fuzzy based REBA methodology in ergonomic risk assessment: An application for service workers. *Engineering Applications of Artificial Intelligence*, 123: 106373. 2023.

[19] Ghasemi, Fakhradin, and Neda Mahdavi. A new scoring system for the Rapid Entire Body Assessment (REBA) based on fuzzy sets and Bayesian networks. *International Journal of Industrial Ergonomics*, 80: 103058, 2020.

[20] Papetti, Alessandra. Preliminary investigation of a wearable device for evaluating muscular effort and fatigue at workplace. *International Journal on Interactive Design and Manufacturing*, 19.5: 3647-3659, 2025.

[21] Mudiyanselage, Srimantha E. Automated workers' ergonomic risk assessment in manual material handling using sEMG wearable sensors and machine learning. *Electronics*, 10(20),: 2558, 2021.

[22] Bassani, Giulia, Alessandro Filippeschi, and Carlo Alberto Avizzano. A dataset of human motion and muscular activities in manual material handling tasks for biomechanical and ergonomic analyses. *IEEE Sensors Journal*, 21.21: 24731-24739, 2021.

Li, X., et al. A framework for evaluating muscle activity during repetitive manual material handling in construction manufacturing. *Automation in Construction*, 79: 39-48, 2017.