Proactive Ergonomic Human Motion Generation for Human-Robot Collaboration

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***Abstract*— This paper presents a framework for generating ergonomically safe human motion in human-robot collaboration , focusing on stance stability and effort alignment. A regressive model predicts human motion from repetitive task data, and a virtual human model tracks this prediction. Control Barrier Functions ensure the motion remains within ergonomic limits. Simulations demonstrate stable posture and efficient force alignment, validating the framework's potential for safe motion generation in dynamic collaborative settings.**

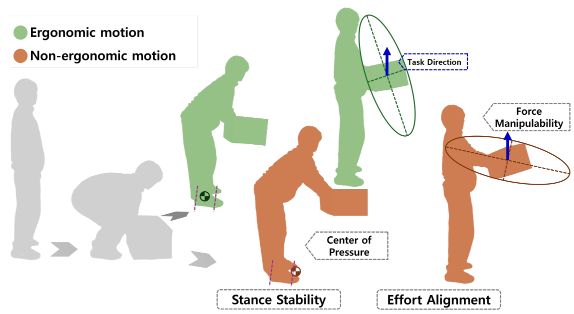

Fig. 1: Comparison between ergonomically safe (green) and unsafe (orange) lifting motions. In the safe motion, stance stability is maintained with the CoP remaining within limits, and effort alignment is achieved as the force manipulability (indicated by ellipsoids at the hand) aligns with the task direction. This comparison highlights how maintaining an *ergonomic safe set* can reduce musculoskeletal risk.

I. INTRODUCTION

Despite advances in automation, many industrial production lines still rely on manual tasks [1]. As shown in Fig. 1, such tasks often involve repetitive movements and awkward postures that increase the risk of work-related musculoskeletal disorders (WMSDs) [2], [3].

Established ergonomic assessment methods, such as NIOSH, RULA, and OCRA [4], have been broadly adopted to evaluate potential hazards in tasks like assembly and lifting. However, because these methods rely on observational or retrospective analyses, sensor-based approaches have been introduced to enable real-time ergonomic assessments [5], [6], [7]. While they provide immediate feedback, preventing non-ergonomic states before they occur remains a challenge.

Recognizing the value of proactive strategies, recent studies have explored predictive models to forecast future ergonomic states in human-robot collaboration (HRC). For instance, statistical models (e.g., HMM, STS-GCN) can anticipate human motion or posture and provide adaptive assistance [8], [9]. However, they do not fully guarantee that the human performer will remain within safe ergonomic boundaries under continuously varying conditions.

To more reliably ensure safety constraints, control strategies such as Control Barrier Functions (CBFs) can keep a system within predefined safe sets [10], [11]. CBFs have proven effective in safety-critical scenarios like lane-keeping and force constraint enforcement, suggesting their potential for managing ergonomic safety in HRC.

Building on these insights, we propose a proactive ergonomic safety framework that integrates a vector auto-regressive (VAR) model to predict

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human ergonomic states—focusing on stance stability and efficient force alignment—and employs CBFs to maintain movements within safe limits. In particular, stance stability is evaluated via the Center of Pressure, and effort alignment is characterized by the major axis of the force manipulability ellipsoid. By combining predictive modeling with safety-critical control, our approach adapts to dynamic human motion and consistently preserves ergonomic safety throughout HRC scenarios.

II. Problem Formulation

The human system is modeled as a joint-space impedance system:

$$\dot{\boldsymbol{\theta}}(t) = \mathbf{A}\boldsymbol{\theta}(t) + \mathbf{B}_d\,\mathbf{q}_{des} + \mathbf{B}_u\,\mathbf{u}(t), \tag{1}$$

where $\boldsymbol{\theta}(t) = [\mathbf{q}(t); \dot{\mathbf{q}}(t)] \in \mathbb{R}^{2n}$. The matrices are

$$\mathbf{A} = \begin{bmatrix} \mathbf{0}_n & \mathbf{I}_n \\ -\mathcal{I}^{-1}\mathbf{K} & -\mathcal{I}^{-1}\mathbf{D} \end{bmatrix}, \quad \mathbf{B}_d = \begin{bmatrix} \mathbf{0}_n \\ \mathcal{I}^{-1}\mathbf{K} \end{bmatrix}, \quad \mathbf{B}_u = \begin{bmatrix} \mathbf{0}_n \\ \mathbf{I}_n \end{bmatrix}.$$

Here, $\mathcal{I}$, $\mathbf{K}$, and $\mathbf{D}$ denote inertia, stiffness, and damping, and $\mathbf{u}(t)$ is the joint torque input. The control objective is to confine the motion within an *ergonomic safe set* defined by (i) stance stability (via CoP), (ii) effort alignment (via force manipulability), and (iii) joint limits.

This is addressed in two stages: (1) predicting future ergonomic states, and (2) generating ergonomic motion.

III. Ergonomic State Prediction

A. Human Joint Angle Prediction

We use a VAR model to forecast joint angles from past data:

$$\mathbf{q}_{\text{var}}(t + j\Delta t) = \sum_{k=1}^{p} \boldsymbol{\Psi}_k\,\mathbf{q}(t - k\Delta t + j\Delta t) + \boldsymbol{\eta}(t + j\Delta t)$$

for $j = 1, \ldots, p$, where p is the lag order, $\boldsymbol{\Psi}_k$ are the coefficients, and $\boldsymbol{\eta}$ is the error. The a-step-ahead prediction, $\mathbf{q}_{\text{var}}(t+a\Delta t)$, is used as $\mathbf{q}_{des}$ in Eq. (1).

B. Stance Stability

Stance stability is assessed via the Center of Pressure (CoP) using a SESC model [12]:

$$\hat{C}_p(\mathbf{q}) = \mathbf{x}_0(\mathbf{q}) + \mathbf{B}^*(\mathbf{q})\,\hat{\boldsymbol{\Phi}}_M,$$

with $\hat{\boldsymbol{\Phi}}_M$ pre-estimated from extra sensors. The estimated CoP is normalized by the midpoint between max/min thresholds $(C_{p,M}, C_{p,m})$:

$$\hat{\bar{C}}_p(\mathbf{q}) = C_p - \frac{C_{p,M} + C_{p,m}}{2}. \tag{2}$$

C. Effort Alignment

Effort alignment is evaluated via force manipulability. The force manipulability ellipsoid is computed as:

$$\mathbf{E}_F(\mathbf{q}) = \mathbf{f}_h^T \left(\mathbf{J}(\mathbf{q})\,\mathbf{J}^T(\mathbf{q})\right)^{-1} \mathbf{f}_h = \mathbf{f}_h^T \mathbf{M} \mathbf{f}_h,$$

where $\mathbf{J}(\mathbf{q})$ is the Jacobian of the human system and $\mathbf{f}_h$ is the task force vector at the hand. The alignment is quantified by the inner product between the principal eigenvector of $\mathbf{M}$, denoted $v(\mathbf{q})$, and the task direction d:

$$y(\mathbf{q}) = d^T v(\mathbf{q}). \tag{3}$$

IV. Proactive Ergonomic Motion Generation

A. Control Barrier Functions

We define the safe set as $\mathcal{C}_b = \{\mathbf{q} \in \mathbb{R}^n \mid h(\mathbf{q}) \geq 0\}$. Separate CBFs are designed for each constraint.

Stance Stability CBF: Using the normalized CoP in Eq. (2), and with $\bar{C}_{p,M} = C_{p,M} - \frac{C_{p,M}+C_{p,m}}{2}$, we define:

$$h_{SS}(\mathbf{q}) = \bar{C}_{p,M} - \operatorname{sgn}(\dot{C}_p)\,\hat{\bar{C}}_p(\mathbf{q}),$$

where $\operatorname{sgn}(\dot{C}_p)$ detects the direction of CoP change.

Effort Alignment CBF: To prevent misalignment through Eq. (3), we define:

$$h_{EA}(\mathbf{q}, \dot{\mathbf{q}}) = \Big(y_M - y(\mathbf{q})\Big) - \frac{1}{2}\frac{\dot{y}^2}{a_{\max}},$$

with $y_M = \cos(\epsilon_{th})$, and $a_{\max}$ is the maximum allowable acceleration.

B. QP Formulation

The optimal control input is obtained by solving the following Quadratic Program (QP):

$$\begin{aligned} \min_{\mathbf{u}(t)} \quad & \|\mathbf{u}(t)\|^2, \\ \text{s.t.} \quad & \ddot{h}_{SS} \geq -\alpha_1\,h_{SS} - \alpha_2\,\dot{h}_{SS}, \\ & \dot{h}_{EA} \geq -\beta_1\,h_{EA}, \\ & \mathbf{q}_{\min} \leq \mathbf{q}(t+1) \leq \mathbf{q}_{\max}, \end{aligned} \tag{4}$$

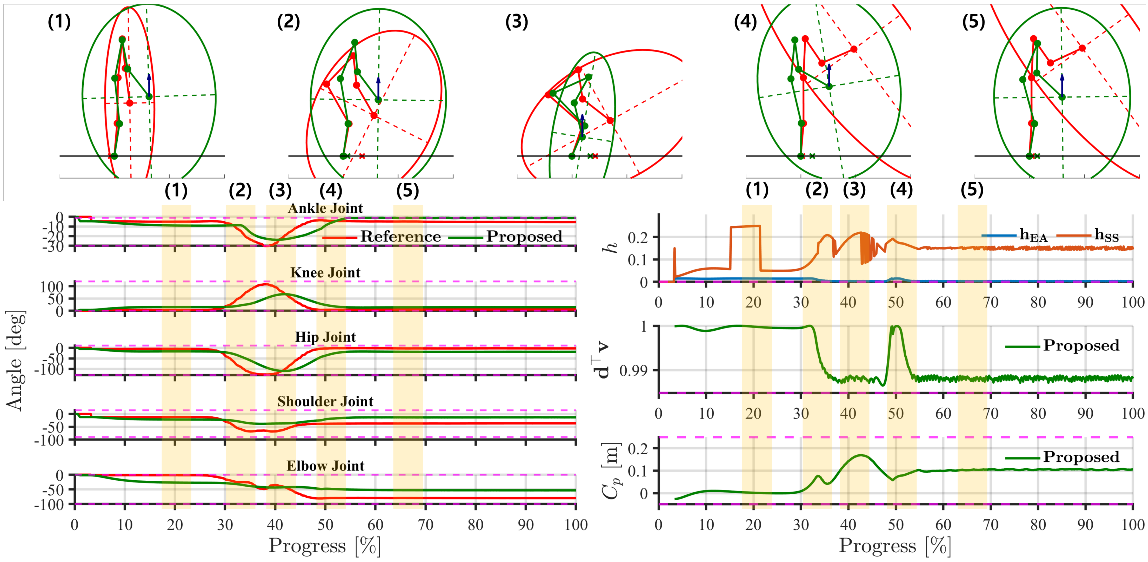

Fig. 2: Overall simulation results. Left: Human motion snapshots based on joint angles (red: reference motion; green: proposed motion). Bottom-left: Joint angle trajectories with dashed lines denoting joint limits. Right: CBF values for ergonomic constraints (top), alignment of force manipulability ellipsoid's major axis direction with task direction (middle), and CoP position within defined safety limits (bottom).

with $\mathbf{q}(t+1) = \mathbf{q}(t) + \dot{\mathbf{q}}(t)dt + \frac{1}{2}\ddot{\mathbf{q}}(t)dt^2$. This formulation (Eq. (4)) enables real-time generation of safe, ergonomic motion trajectories.

V. SIMULATION

A. Simulation Setups

Simulations were conducted in MATLAB using lifting data from two subjects (63 trials, 1 loss) captured via Xsens sensors. Fifty-nine trials were used to train a VAR model ($p = 21$, $a = 5$) for joint angle forecasts at 60 Hz.

The human system is modeled as a joint-space impedance model with $\mathcal{I} = \mathbf{I}_n$, $\mathbf{K} = 100\mathbf{I}_n$, $\mathbf{D} = 20\mathbf{I}_n$, and $dt = 0.05\,\mathrm{s}$. The CoP was estimated assuming an external load $m_e = 3$ kg, with joint limits $\mathbf{q}_{\min} = [-30, 0.5, -130, -90, -100]^\circ$ and $\mathbf{q}_{\max} = [-1, 120, 10, 15, 0.5]^\circ$, and a CoP range set to $[-0.05, 0.25]$ m. Effort alignment was enforced by aligning the major axis of the force manipulability ellipsoid at the hand with the task direction $d = [0, 1]^T$ ($\epsilon_{th} = 10^\circ$). CBF gains were set to $\alpha_1 = 400$, $\alpha_2 = 40$ (stance stability) and $\beta_1 = 20$, $a_{max} = 100\,\mathrm{s}^{-2}$ as specified in Eq. (4).

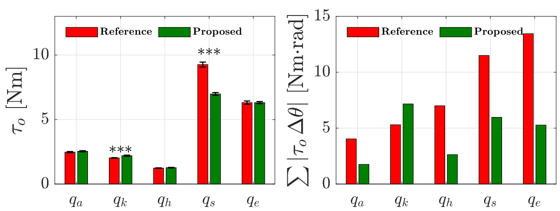

Fig. 3: Overloading Joint Torque (τ_o) Analysis. Left: Mean $|\tau_o|$ with standard error. Asterisks "***" denote statistically significant differences ($p < 0.001$). Right: Cumulative absolute mechanical energy calculated as $\sum |\tau_o \cdot \Delta q|$, representing total biomechanical effort per joint.

B. Simulation Results

Fig. 2 shows that the proposed method closely tracks the reference motion while enforcing joint limits. The top-left snapshots display the reference and proposed motions, with hand ellipsoids representing force manipulability. The bottom-left plots confirm that joint angles remain within safe bounds, while the right panels indicate that CBF values are maintained positive, the manipulability direction consistently aligns with the task, and the CoP stays within ergonomic limits.

To quantify joint loading, we computed the absolute overloading joint torque, τ_o, and derived its mean magnitude, $\overline{|\tau_o|}$, for each joint. As shown in Fig. 3 (left), paired t-tests reveal significant reductions ($p < 0.001$) in τ_o for the shoulder, while the ankle, hip, and elbow show no significant change. Notably, the knee exhibits an increase in $\overline{|\tau_o|}$ under the proposed method. Similarly, the cumulative mechanical energy,

$$E = \sum_{k=1}^{N-1} |\tau_o(k)\Delta q(k)|,$$

is reduced for most joints; however, the knee displays higher energy than the reference. This suggests that although the proposed framework effectively reduces joint stress overall, compensatory load redistribution may lead to increased loading at the knee—a trade-off warranting further investigation.

Overall, these results demonstrate that the proposed method significantly decreases joint stress and cumulative biomechanical effort, thereby enhancing ergonomic safety during repetitive lifting tasks.

VI. CONCLUSION

This paper presented a framework for generating human motion that enhances ergonomic safety using predicted future states and Control Barrier Functions (CBFs). Stance stability is maintained by applying CBFs to the Center of Pressure (CoP), while effort alignment is achieved by aligning the force manipulability ellipsoid's major axis at the hand with the task direction.

Simulation results show that the proposed method keeps motion within safe ergonomic limits. Analysis of the overloading joint torque (τ_o) reveals a significant reduction at the shoulder ($p < 0.001$), while the ankle, hip, and elbow remain statistically unchanged. Notably, the knee exhibits increased mean τ_o and cumulative energy, suggesting compensatory load redistribution that warrants further refinement.

Despite a slight delay due to 5-step-ahead prediction, the method remains stable and constraint-satisfying. Future work will explore longer prediction horizons to improve responsiveness and will validate the framework in real-world human-robot collaboration experiments.

REFERENCES

[1] D. Jayasekara, N. Y. G. Lai, K.-H. Wong, K. Pawar, and Y. Zhu, "Level of automation (loa) in aerospace composite manufacturing: Present status and future directions towards industry 4.0," *Journal of Manufacturing Systems*, vol. 62, pp. 44–61, 2022.

[2] A. Yassi, "Repetitive strain injuries," *The Lancet*, vol. 349, no. 9056, pp. 943–947, 1997.

[3] P. Brooks, "Repetitive strain injury." *BMJ: British Medical Journal*, vol. 307, no. 6915, p. 1298, 1993.

[4] G. C. David, "Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders," *Occupational medicine*, vol. 55, no. 3, pp. 190–199, 2005.

[5] S. Proia, R. Carli, G. Cavone, and M. Dotoli, "Control techniques for safe, ergonomic, and efficient human-robot collaboration in the digital industry: A survey," *IEEE Transactions on Automation Science and Engineering*, vol. 19, no. 3, pp. 1798–1819, 2021.

[6] W. Kim, J. Lee, N. Tsagarakis, and A. Ajoudani, "A real-time and reduced-complexity approach to the detection and monitoring of static joint overloading in humans," in *2017 International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2017, pp. 828–834.

[7] M. Lorenzini, W. Kim, E. De Momi, and A. Ajoudani, "A new overloading fatigue model for ergonomic risk assessment with application to human-robot collaboration," in *2019 International Conference on Robotics and Automation (ICRA)*. IEEE, 2019, pp. 1962–1968.

[8] H. Liu and L. Wang, "Human motion prediction for human-robot collaboration," *Journal of Manufacturing Systems*, vol. 44, pp. 287–294, 2017.

[9] M. Billast, J. De Bruyne, K. Bombeke, T. De Schepper, and K. Mets, "Physical ergonomics anticipation with human motion prediction." SciTePress, 2024.

[10] A. D. Ames, S. Coogan, M. Egerstedt, G. Notomista, K. Sreenath, and P. Tabuada, "Control barrier functions: Theory and applications," in *2019 18th European control conference (ECC)*. IEEE, 2019, pp. 3420–3431.

[11] A. D. Ames, X. Xu, J. W. Grizzle, and P. Tabuada, "Control barrier function based quadratic programs for safety critical systems," *IEEE Transactions on Automatic Control*, vol. 62, no. 8, pp. 3861–3876, 2016.

[12] W. Kim, L. Peternel, M. Lorenzini, J. Babič, and A. Ajoudani, "A human-robot collaboration framework for improving ergonomics during dexterous operation of power tools," *Robotics and Computer-Integrated Manufacturing*, vol. 68, p. 102084, 2021.