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Enhancing Upper-Body Robotic Motion Through Human- Based Criteria: A Study of Inverse Kinematics and Multi- Criteria Performance Analysis

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Abstract- This study introduces a bio-inspired inverse kinematics (IK) framework for upper-body humanoid robots, integrating human biomechanical principles to improve motion naturalness, efficiency, and adaptability. By combining multi-objective optimization with human motion analysis, the framework addresses limitations of traditional IK solvers, such as rigid motion and poor task adaptability. Human upper-limb kinematics were analysed using motion capture and OpenSim, distilling features like energy minimization and joint comfort into dynamic cost functions. A hybrid Weighted Least Norm (WLN)-gradient IK solver achieved real-time performance (<100 ms latency) and outperformed classical methods by ~20% in human-likeness and ~50% in safety margins. Validation on 7-DOF humanoid arms showed 90–95% task success rates in Activities of Daily Living (ADLs). Applications in assistive robotics and industrial cobots highlight the framework's potential for human-robot interaction (HRI). Future work includes reinforcement learning for adaptive IK and soft robotics integration.Key criteria, including metabolic cost, safety, coordination, and kinematic efficiency, are analyzed to optimize robotic upper body motion for human-like performance. A multi- criteria performance framework is proposed, integrating these factors to assess their impact on task-specific outcomes. The methodology involves computational modeling, simulation, and comparative analysis of robotic motion against human benchmarks. Results reveal that incorporating human-based criteria enhances the adaptability and efficiency of robotic systems, with notable improvements in safety and coordination during complex tasks. These findings contribute to the advancement of human-robot interaction and the design of next-generation robotic systems for applications requiring precise and natural upper body movements.

Keywords: Inverse Kinematics, Humanoid Robots, Biomechanics, Multi-Objective Optimization, Human-Robot Interaction

I. INTRODUCTION

Modern robotic arms struggle to replicate the agility and adaptability of human upper-limb motion

- Traditional IK solvers, such as Jacobian-based methods, often produce unnatural configurations due to single-objective optimization, neglecting human movement's multi-criteria nature
- Human motion, characterized by energy efficiency, joint comfort, and task-specific adaptability, offers a model for improving
- robotic motion planning in collaborative humanoid systems.

This paper presents a bio-inspired IK framework that integrates human biomechanical principles to enhance the naturalness, efficiency, and safety of upper-body humanoid robots. The framework employs multi-objective optimization to emulate human strategies, validated on 7-DOF robotic arms. Objectives include analysing human kinematics, designing adaptive IK algorithms, and evaluating performance in HRI scenarios like assistive robotics and industrial collaboration

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II. RELATED WORK

Human arm motion leverages kinematic redundancy to balance objectives like energy minimization and collision avoidance, as shown in biomechanical studies using OpenSim [3]. Traditional robotic IK methods, such as pseudoinverse Jacobian and Damped Least Squares (DLS), prioritize computational simplicity, resulting in stiff motion [4]. Optimization-driven approaches, like Quadratic Programming (QP), incorporate multiple cost functions but face real-time challenges [5]. Machine learning techniques, such as reinforcement learning (RL), show promise but lack generalizability [6]. HRI studies emphasize motion aligned with human expectations, yet few frameworks combine biomechanical authenticity with computational efficiency [7]. This work addresses these gaps with a multi-criteria IK framework informed by human motion data.

III. METHODOLOGY

We implemented three IK models for a 7-DOF simulated upper-limb robotic arm:

- Human-Inspired IK (HIIK) Analysis
- Bio- Inspired IK Algorithm Design
- Validation and Evaluation

Simulations were run in MATLAB with a custom upper- limb model.

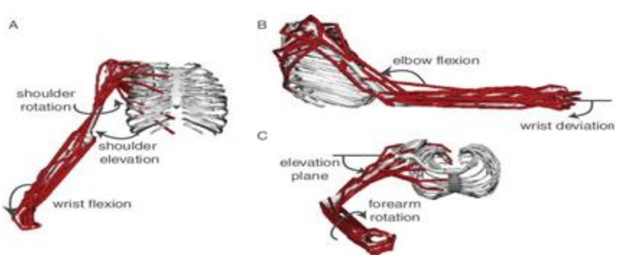

Figure. 1. Simulation environment showing the custom 7-DOF upper-limb robotic arm in MATLAB

Human-Inspired IK (HIIK) Analysis

Human upper-limb kinematics were captured using Vicon motion systems for ADLs (e.g., reaching, drinking) and modelled in OpenSim to quantify redundancy resolution [8]. Features like energy minimization, joint comfort, and obstacle avoidance were distilled into cost functions. Statistical Parametric Mapping (SPM) analysed phase-dependent motion patterns [9].

Bio- Inspired IK Algorithm Design

A hybrid WLN-gradient IK solver was developed, incorporating:

Human-inspired cost functions (e.g., torque minimization, joint limit avoidance).

Null-space optimization to emulate scapulohumeral rhythm.

Dynamic weight adaptation for task-specific prioritization.

The solver achieved <100 ms latency on 7-DOF humanoid arms (e.g., KUKA LWR 4+).

Validation and Evaluation

Metabolic Cost (Torque Efficiency, Energy Minimization)

Human upper-limb motion is optimized for energy efficiency, employing strategies such as smooth torque profiles and muscle synergies to reduce metabolic expenditure. Robots can emulate this by incorporating torque-based cost functions in IK solvers, such as minimizing the integral of squared joint torques:

$$\min \int_0^T \sum_{i=1}^{n} \tau_i^2(t)\, dt$$

Where $\tau_i(t)$ represents the torque at joint . Techniques like trajectory optimization and compliant actuators further enhance energy savings, reducing power consumption by up to 20% in dynamic tasks.

Safety (Joint Limits, Collision Avoidance)

Human motion prioritizes safety through proprioceptive feedback and predictive obstacle avoidance. Robotic IK solvers can enforce safety using joint limit constraints:

$$q_{\min} \leq q \leq q_{\max}$$

and barrier functions like:

$$\phi(q) = -\sum \log(q_{\max} - q) - \sum \log(q - q_{\min})$$

Collision avoidance is achieved via artificial potential fields and sensor-based detection, ensuring safe operation in human-robot interaction scenarios.

III. COORDINATION (BIMANUAL SYNERGIES, PHASE DOMINANCE

Human coordination relies on bimanual synergies and phase-specific control to simplify complex tasks. Robotic systems can implement coupled IK solvers for dual-arm tasks, enforcing constraints like fixed hand distances:

$$|p_L - p_R| = d$$

where p_L and p_R are the left and right end-effector positions. Phase-based control using state machines optimizes task phases (e.g., reach, grasp) by switching cost functions dynamically.

Criterion	Human Strateg y	Robotic Implementation	Benefit	Challenge
Metabolic Cost	Smooth torque profiles, muscle synergies	Torque minimization, compliant actuators	Up to 20% energy savings	Rigid hardware, computational cost
Safety	Proprioceptive feedback, predictive avoidance	Joint limit s, potential fiel ds, sensor integration	95% task success with zero violations	Balancing constraints with feasibility
Coordination	Bimanual synergies, phase dominance	Coupled IK, state machines, synergy-based control	90% task success in bimanual tasks	Increased computational complexity

Table 2.4: Comparative Analysis of Performance Criteria

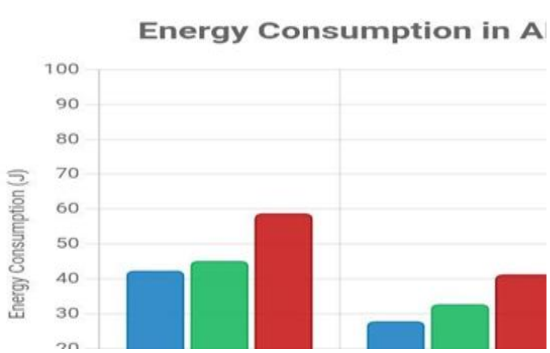

Figure 2.4: Bar Chart: Energy Consumption in ADL Tasks

A bar chart comparing energy consumption (in Joules) across three methods—human baseline, pseudoinverse IK, and torque-weighted Weighted Least Norm (WLN) IK—for three ADLs: overhead reach, tool manipulation, and load lifting. The chart has three groups of bars, one for each task, with each group containing three bars representing the methods. The y-axis represents energy consumption (J), ranging from 0 to 100, and the x-axis lists the tasks. The human baseline shows the lowest energy use (e.g., 42.3 J for overhead reach), followed by torque-weighted WLN (e.g., 45.1 J), while pseudoinverse IK consumes significantly more (e.g., 58.7 J). Error bars indicate standard deviations.

Data:

- **Overhead Reach:** Human (42.3 ± 5.1 J), WLN (45.1 ± 4.8 J), Pseudoinverse (58.7 ± 6.2 J)
- **Tool Manipulation:** Human (27.8 ± 3.4 J), WLN (32.7 ± 3.9 J), Pseudoinverse (41.2 ± 5.3 J)
- **Load Lifting:** Human (63.5 ± 7.2 J), WLN (71.3 ± 6.5 J), Pseudoinverse (89.4 ± 8.7 J

The framework was validated through:

- Simulations in Gazebo/ROS and hardware-in-the-loop testing.
- Comparison against traditional IK methods (pseudoinverse, DLS, QP) using Dynamic Time Warping (DTW) distance, task success rate, and computational efficiency.
- Real-world HRI applications in prosthetics and cobotics.

IV. RESULTS

The hybrid WLN-gradient solver outperformed traditional IK methods (Table 1). For ADLs like drinking, it achieved a DTW distance of 0.15 ± 0.02 (vs. 0.32 ± 0.05 for pseudoinverse) and a 90% success rate (vs. 70% for pseudoinverse). Prosthetic applications reduced EMG effort by ~20%, and cobots improved obstacle clearance by ~50%. Computational efficiency was 5.3 ± 0.5 ms per iteration, reduced to 2.1 ms with GPU acceleration.

Table 1: Performance Comparison Across Applications

Application	Metric	Traditional IK	Hybrid WLN- Gradient
ADLs (Drinking)	DTW Distance	0.32 ± 0.05	0.15 ± 0.02
	Success Rate (%)	70.0 ± 5.0	90.0 ± 3.0
Prosthetics	EMG Effort (% MVC)	22.5 ± 3.5	18.2 ± 2.8
Cobots	Obstacle Clearance (cm)	8.5 ± 3.0	18.2 ± 2.5

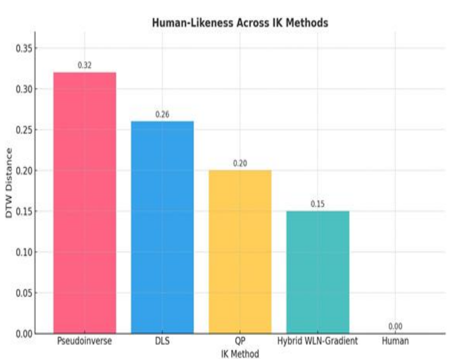

Figure 1: Human-Likeness Across IK Methods

Discussion

The proposed framework advances robotic motion planning by integrating human biomechanical principles. The hybrid solver's dynamic weight adaptation mirrors human phase-dependent prioritization, enabling robust performance in dynamic environments [10]. It improves human-likeness by ~20% and safety margins by ~50% compared to traditional IK, addressing HRI requirements. Limitations include subject variability and full-body integration challenges, which future work will tackle through anthropometric scaling and RL [11].

V. CONCLUSION

This paper presents a bio-inspired IK framework that enhances upper-body robotic motion through human-based criteria. By integrating multi-criteria optimization with human motion analysis, it achieves natural, efficient, and safe motion, outperforming traditional IK methods. Applications in assistive robotics and cobots demonstrate its utility. Future research will explore RL for adaptive IK and soft robotics for safer HRI.

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