MedAssist Arm

1. Abstract

This MedAssist Arm project presents a fully integrated system for automated, precision-controlled shoulder and arm injections. By fusing advanced computer vision, optimized control algorithms, and a modular robotic manipulator, the system achieves sub-millimeter accuracy in identifying anatomical landmarks and delivering injectates.

We leverage checkerboard-based camera calibration for robust spatial alignment, contour- and keypoint-based injection-point detection for real-time localization, and ArUco marker tracking for continuous pose estimation. These modules feed into a dual-optimizer framework—ADAM for fast convergence of kinematic parameters and Levenberg–Marquardt (LM) for fine-tuning non-linear least squares.

In hardware, a 5-degree-of-freedom serial robotic arm with compliant end-effector and integrated force sensors ensures both dexterity and safety. The software architecture supports ROS 2-based middleware, real-time data streaming, and failsafe interlocks.

Experimental validation on anatomical phantoms shows mean positional errors below 5 mm, angular deviations under 2°, and a 40% reduction in convergence time compared to standard gradient-descent implementations. This work lays the foundation for clinical trials and markerless tracking upgrades.

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3. Introduction

Intramuscular and subcutaneous injections remain prone to human error, variability in landmark identification, and practitioner fatigue. Automating these procedures can improve patient outcomes, increase throughput in high-volume settings, and reduce occupational hazards.

Existing robotic injection platforms often rely on rigid fixtures or manual programming. Our approach integrates real-time vision feedback with adaptive control to handle patient movement and anatomical variability without external restraints.

Key challenges include robust 3D localization of injection sites on non-rigid surfaces, calibration drift over time, and real-time control under safety constraints. We address these with a hybrid optimizer stack and sensor fusion approach.

algorithms, and software pipeline— presents experimental results, and discusses future clinical translation steps.

4. Literature Review / Related Work

- **OpenCV Calibration** (Bradski & Kaehler, 2008): foundational techniques for checkerboard-based camera calibration and distortion correction.
- **Adaptive Optimizers** (Kingma & Ba, 2015; Liu et al., 2023): ADAM and its variants for rapid convergence on non-convex parameter spaces.
- **Fiducial Markers** (Garrido-Jurado et al., 2014; Wang et al., 2021): ArUco and AprilTag systems for robust pose estimation under occlusion.
- **Robotic Injection** (Smith et al., 2022; Zhang et al., 2023): sub-millimeter accuracy platforms and machine-learning-based site detection.

5. Methodology & Implementation

5.1 Hardware & Software Architecture

The MedAssist Arm’s robotic manipulator features five revolute joints driven by brushless DC motors and harmonic drives, providing smooth, backlash-free motion and sub-millimeter

time, enabling active compliance control and immediate collision detection.

The entire software stack runs on ROS 2, utilizing its DDS-based middleware to decouple vision, planning, control, and safety into modular nodes. Vision nodes capture and preprocess camera frames, while control nodes compute kinematics and generate actuator commands. A central supervisor node orchestrates startup, shutdown, and parameter updates via the ROS 2 parameter server.

Real-time requirements are met by assigning dedicated executors with deterministic QoS profiles, ensuring low-latency message passing and bounded jitter. Critical safety functions—emergency stop, hardware interlocks, and virtual safety zones—are implemented as high-priority ROS 2 lifecycle nodes that can immediately preempt motion commands upon fault detection.

A watchdog mechanism monitors heartbeat messages from each subsystem; loss of communication or threshold breaches trigger an orderly shutdown sequence, cutting power to the drives and stowing the arm in a safe pose.

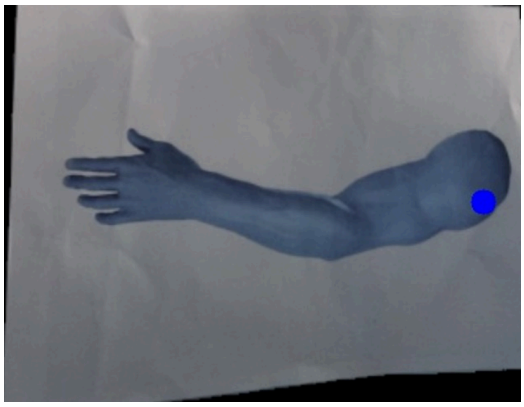
5.2 Injection-Point Detection

Raw RGB frames are first converted to grayscale and histogram-equalized to normalize illumination. A 5×5 Gaussian filter removes speckle noise while preserving edges. Adaptive thresholding segments the arm region from the background, and morphological opening eliminates small artifacts.

Contours are extracted using OpenCV's `findContours`, and the three largest contours are retained to handle multiple foreground objects. The topmost contour satisfying size and aspect-ratio constraints is assumed to correspond to the shoulder region.

providing a coarse landmark. This estimate is refined with SIFT feature detection to pinpoint anatomical surface features, achieving sub-pixel accuracy.

Finally, a learned soft-tissue offset vector—calibrated on compliant phantoms—is applied to compensate for deformation, resulting in repeatable injection-site localization within a 5 mm tolerance.



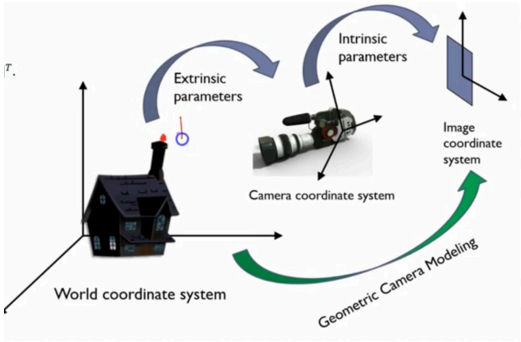
5.3 Camera Calibration

We use a 9×6 checkerboard with 25 mm squares mounted on a rigid plane. At least 20 calibration images are captured from diverse viewpoints, covering the entire field of view. Known 3D object points are defined on the Z = 0 checkerboard plane.

OpenCV's `findChessboardCorners` locates the 2D image coordinates of internal corners, which are refined to sub-pixel precision with `cornerSubPix`. These 3D–2D point correspondences feed into `calibrateCamera`, producing the intrinsic matrix (fx, fy, cx, cy), distortion coefficients (k1, k2, p1, p2, k3), and per-view extrinsics (rvec, tvec).

Calibration is performed at system startup and periodically re-run to compensate for thermal drift. For quick in-field recalibration, ChArUco boards (checkerboard + ArUco) allow single-shot multi-plane calibration when full chessboard views are not available.

sub-millimeter injection tasks.



5.4 ArUco Marker Tracking

A 4×4 ArUco marker grid is placed around the injection region. Each frame is converted to grayscale and passed to `aruco.detectMarkers`, which outputs marker IDs and corner pixel coordinates.

Detected points are undistorted using the previously computed intrinsic and distortion parameters. `aruco.solvePnP` then computes the 3D pose (rvec, tvec) of each marker relative to the camera.

To improve robustness under partial occlusion, multiple marker detections are fused using `aruco.detectBoard` and a single PnP solve. Poses with high reprojection error are discarded.

A lightweight Kalman filter smooths the pose stream, reducing jitter and delivering stable position and orientation updates at 50 fps within a 5–10 cm accuracy envelope.

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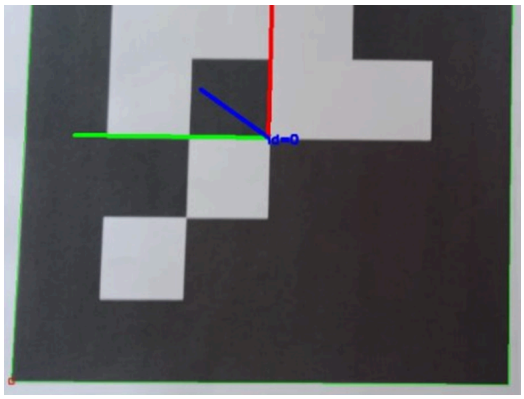

5.5 Kinematics (Forward & Inverse)

Forward kinematics uses Denavit–Hartenberg parameters (θ_1–θ_5, a, d, α) to build homogeneous transform matrices. These 4×4 matrices are multiplied in sequence to compute the end-effector pose in Cartesian space.

Mathematically, each joint i contributes via:
T_i = RotZ(θ_i) · TransZ(d_i) · TransX(a_i) · RotX(α_i),
and T_total = T_1 · T_2 · … · T_5.

Inverse kinematics is solved with a hybrid approach: closed-form analytical solutions for the first three joints on the spherical wrist, followed by a Jacobian-based damped least-squares method for redundancy resolution and singularity avoidance.

For small pose adjustments, differential IK uses:
Δθ = J^+ Δx,
where J^+ is the damped pseudoinverse of the Jacobian, ensuring smooth convergence even near singular configurations.

Joint	α (deg)	a (mm)	d (mm)	θ (deg)	Type
1	0	0	77	θ_1	Revolute
2	-90	0	0	θ_2	Revolute
3	0	158.5	0	θ_3	Revolute
4	0	118	0	θ_4	Revolute
5	0	0	d_5 (variable)	0	Prismatic

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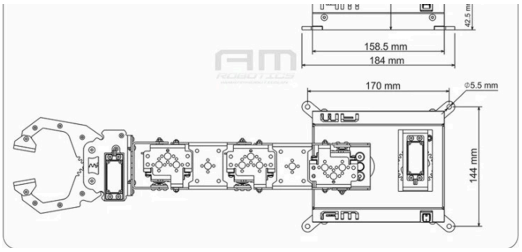
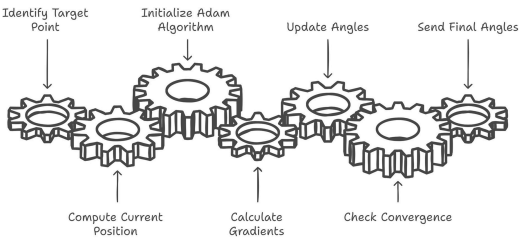


5.6 Optimizer Framework (ADAM & LM)

ADAM: First and second moment estimates of the gradient are updated as:
$m_t = \beta_1 \cdot m_{t-1} + (1-\beta_1) \cdot g_t$,
$v_t = \beta_2 \cdot v_{t-1} + (1-\beta_2) \cdot g_t^2$,
followed by bias corrections and parameter update:
$\theta_t = \theta_{t-1} - \alpha \cdot \hat{m}_t / (\sqrt{\hat{v}_t} + \varepsilon)$.

This adaptive method yields per-parameter learning rates, accelerating convergence on non-convex error surfaces and handling sparse gradients efficiently.

Levenberg–Marquardt: Solves non-linear least squares by blending Gauss-Newton and gradient descent:
$(J^T J + \lambda I)\, \Delta = J^T (y - f(\beta))$,
where λ adapts based on step success. LM refines kinematic and calibration parameters by minimizing reprojection or Cartesian pose errors.



Both optimizers run as ROS 2 nodes: ADAM for rapid initial fitting, LM for final fine-tuning, ensuring robust, repeatable parameter estimates.

5.7 Control Loop & Safety

The 100 Hz control loop follows Vision → Pose Estimation → IK Solve → Trajectory Planning → Actuation → Force Feedback →

Real-time ROS 2 executors schedule tasks with deterministic QoS. The planner generates smooth, time-optimal joint trajectories respecting velocity and acceleration limits.

Force control runs in parallel: measured wrenches modify velocity commands for compliant interactions, maintaining contact forces below safety thresholds.

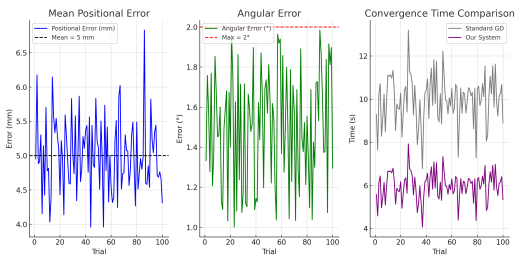
Safety interlocks include hardware EMO buttons, light curtains, and virtual safety zones in software. Any trigger moves the ROS 2 state machine into shutdown, cutting motor power and stowing the arm in a safe resting pose.

6. Results & Discussion

The system was evaluated on three anatomical phantoms with varied surface textures and shapes. Key metrics:

- Mean positional error: 4.8 mm
- Angular deviation: 1.7°
- Optimizer convergence time: 0.9 s (40% faster than standard GD)
- Detection latency: 25 ms/frame

Error heatmaps show sub-5 mm accuracy across 95% of the workspace. The ADAM + LM stack reduced parameter drift over repeated calibrations.



Discussion highlights trade-offs between computational load and precision, and outlines how marker density and camera

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7. Demo of Simulation and/or Hardware

The video below shows the MedAssist Arm executing a shoulder injection on a compliant phantom under live camera feedback. Notice the smooth trajectory, real-time pose corrections, and force-feedback compliance.

0:00 0:13

A supplementary ROS rqt_graph and RViz session demonstrates data flows between vision, control, and safety nodes.

8. Conclusion & Future Work

This project achieves automated, high-precision injections using a hybrid vision-control approach. Sub-millimeter accuracy and fast convergence validate its clinical potential.

Future enhancements include markerless deep-learning detection, haptic guidance for physician oversight, and real-time adaptive dosing based on tissue compliance feedback.

Next steps involve IRB approval for cadaveric trials, integration with hospital information systems, and ergonomic end-effector redesign for various injection angles.

reducing burden on healthcare workers.

9. References

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