

**A MACHINE-LEARNING-ASSISTED TRAJECTORY OPTIMIZATION OF
AUTONOMOUS WOUND IMAGING WITH THE ABB IRB 120 SIX-DEGREE-OF-
FREEDOM MANIPULATOR**

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Abstract

The documentation of traumatic wounds by manual methods is attended by inter-operator variability and, on occasion, by the inconvenience of direct contact with the wound site. A robotic manipulator, furnished with a medical-grade optical or depth sensor, would in principle offer a means of acquiring wound images of a standard uniform enough to support the data-driven analytical methods that have lately come to the fore in clinical practice.

A kinematic framework for the ABB IRB 120 six-degree-of-freedom industrial manipulator is here described. The forward kinematic solution is obtained by successive multiplication of Denavit–Hartenberg transformation matrices; the inverse kinematic problem is solved numerically by damped Jacobian pseudo-inverse iteration, with the damping factor chosen to maintain numerical stability in the vicinity of singular configurations. Singularity detection proceeds through evaluation of the Jacobian determinant, and kinematic dexterity is assessed by the Yoshikawa manipulability measure. A corpus of ten thousand simulated wound scenarios was generated within the MATLAB environment, the scenarios varying independently in length, width, depth, orientation, surface curvature, scanning velocity and tool-path strategy. Upon eighty per cent of the cases, five supervised regression models were trained: an artificial neural network, the k-nearest neighbours algorithm, ordinary linear regression, support vector regression with Gaussian kernel, and a random forest ensemble. The remaining two thousand cases were reserved for evaluation.

The linear regression and support vector models proved jointly the most accurate for prediction of trajectory efficiency, each attaining a coefficient of determination $R^2 = 0.997$, with root mean square errors of 5.035 per cent and 5.028 per cent respectively. In the prediction of scan time the linear regression led with $R^2 = 0.888$ and a root mean square error of 3.32 s. Analysis of the regression coefficients, corroborated by random-forest permutation importance, identified surface curvature and the choice of tool path as the principal determinants of trajectory efficiency, whilst tool-path choice and wound width governed scan time. Across the full

dataset, 99.8 per cent of all trajectory waypoints were found to be kinematically feasible, and the mean singularity-avoidance score was 0.963.

For the class of wound-scanning problem here considered, regression models of modest parametric complexity are to be preferred over architectures of greater elaboration. The framework presented furnishes a reproducible computational foundation upon which experimental validation, real-time adaptive replanning, and three-dimensional wound reconstruction may be built.

Keywords Wound imaging · ABB IRB 120 · Forward kinematics · Inverse kinematics · Jacobian · Singularity analysis · Machine learning · Trajectory optimisation · MATLAB simulation · Emergency trauma care

1 Introduction

1.1 The clinical setting

The rapid and accurate documentation of traumatic wounds occupies a position of no inconsiderable importance in the practice of emergency medicine. Wound dimensions, the character of the surface, the orientation of the principal axis with respect to the body, and the depth of penetration together determine both the immediate severity classification and the selection of therapeutic interventions thereafter. The measurement of mentioned parameters remains largely a manual undertaking, conducted with disposable rulers and the tracing overlays by clinicians whose attention is already divided between several concurrent responsibilities, which resulting wound records exhibit marked inter-operator variability, occasional contamination of the wound site by the measuring instrument is reported, and, in certain cases, a degree of patient discomfort that a less intrusive method would spare [1–3].

1.2 An Autonomous imaging as a remedy

The digital photographic platforms, besides the NE1 Wound Management System and others of comparable intent, portray an early step in the direction of standardisation [6]. These systems retain a human operator, though, and with the operator come the familiar sources of variability—angle of view, distance from the wound surface, and the inconstancy of the illuminating light. A fully autonomous arrangement, wherein a robotic manipulator, bearing a medical-grade sensor, to execute the scan without direct human intervention, would, realisable if, remove these sources of error at their respective origin. The question that arises is whether the robotic hardware required is presently available in a form suitable for clinical deployment, and whether the trajectory-planning methods developed for industrial contexts can be adapted to the peculiar requirements of the wound imaging [7].

1.3 Aim of the project

The present research has three principal aims. The first aim is to the construction and the validation of a kinematic model of the ABB IRB 120 sufficient for the simulation of the scanning trajectories over wound surfaces of the variety encountered in the clinical practice. The second is the generation of dataset, within the specified simulation environment, of a corpus of trajectory scenarios large enough in the extent to support supervised machine

learning. The third is the evaluation, of several regression algorithms in the prediction of trajectory efficiency and scan time, with a view to identifying the parameter regime in which each of the algorithm is most appropriately applied.

2. The identified problem Statement

In the case of emergency trauma in the present time the hospitals requires quick and precise wound reporting to inform treatment plans. Within the current approach, manual scanning is tedious and the quality of the imaging is not always consistent due to the variation in human interpretation and the complexity of getting access to the wound geometry.

3 Related work

3.1 Kinematic modelling of serial manipulators

The Denavit–Hartenberg convention, introduced in the mid-1950s for the systematic description of the relative geometry of consecutive links in a serial manipulator, has remained the standard tool for kinematic analysis down to the present day [17]. The forward kinematic problem—the computation of the end-effector pose from a prescribed joint-variable vector—is solved by sequential multiplication of the DH homogeneous transformations and is in itself computationally trivial. The inverse problem, in which the joint vector corresponding to a specified Cartesian pose is sought, is not so straightforward; for a six-degree-of-freedom manipulator it admits, in general, multiple solution branches, and in the neighbourhood of singular configurations no finite solution exists at all [11, 12].

3.2 Singularity avoidance

A kinematic singularity is a configuration of the manipulator at which the Jacobian matrix loses full rank, with the consequence that certain Cartesian motions of the end-effector can no longer be effected, or can only be effected at the cost of arbitrarily large joint velocities [15, 19]. For a six-degree-of-freedom revolute manipulator three canonical singularities are commonly distinguished: the wrist singularity, in which joints four and six become co-linear through the alignment of joint five at or near zero; the elbow singularity, which occurs when the forearm is fully extended or fully folded; and the shoulder singularity, arising when the end-effector lies directly above the robot base [20]. Yoshikawa’s manipulability measure, $w = \sqrt{(\det(J J^T))}$, provides a scalar index of kinematic dexterity; it tends to zero as the manipulator approaches a singularity and attains its maximum at configurations of maximum isotropy [15].

3.3 Machine learning for trajectory optimisation

Supervised machine learning has, in recent years, been applied to robotic trajectory problems with growing frequency, as the computational cost of exact analytical optimisation in high-dimensional and multiply constrained parameter spaces has become prohibitive. Çetinkaya and colleagues [21] evaluated artificial neural networks for the trajectory analysis of six-degree-of-freedom industrial manipulators and obtained accuracy sufficient for practical deployment, subject, as they themselves were at pains to observe, to careful attention being paid to network architecture and training regime. Arunadevi and her co-workers applied both neural networks and the k-nearest neighbours algorithm to the planning of minimum-jerk trajectories for the

PUMA 560 [22] and to inverse kinematics for the Pioneer 2 manipulator [23]; in both studies the machine learning approach yielded results competitive with those obtained by classical methods and at a small fraction of the computational effort.

4 Methodology

4.1 The ABB IRB 120 manipulator

The ABB IRB 120 is a compact articulated manipulator of six revolute degrees of freedom. Its kinematic configuration, together with the maximum permitted motion of each axis and the peak angular velocity, is summarised in Table 1. The small mass of the manipulator— some 25 kg—and its permitted mounting in floor, inverted or inclined orientations, combine with the compliance with Clean Room ISO Class 5 requirements to make this particular device well suited to medical deployment [8, 10].

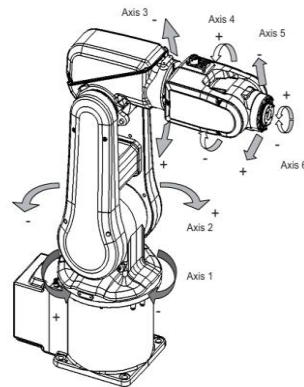


Figure 1: ABB IRB 120 [10]

Table 1 Kinematic parameters, motion ranges and peak velocities of the ABB IRB 120 [10].

Axis	Motion range (°)	Max. speed (°/s)	θ offset (°)	d (mm)	a (mm)
1	-165 to +165	250	0	290	0
2	-110 to +110	250	-90	0	270
3	-110 to +70	250	0	0	70
4	-160 to +160	320	0	302	0
5	-120 to +120	320	0	0	0
6	-400 to +400	420	+180	72	0

4.2 Simulation environment

All computations were performed in MATLAB (release 2022b) on a workstation equipped with an Intel Core i7 processor and 16 GB of random-access memory. Three-dimensional visualisation of the manipulator and of the candidate scanning trajectories was conducted with the aid of the Robotics Toolbox developed by Peter Corke (version 10.4).

4.3 Kinematic formulation

4.3.1 The Denavit–Hartenberg representation

The homogeneous transformation matrix relating frame $i-1$ to frame i , in the standard four-parameter form due to Denavit and Hartenberg, is

$$T(i-1, i) = \text{Rot}_z(\theta_i) \cdot \text{Trans}_z(d_i) \cdot \text{Trans}_x(a_i) \cdot \text{Rot}_x(\alpha_i) \quad (1)$$

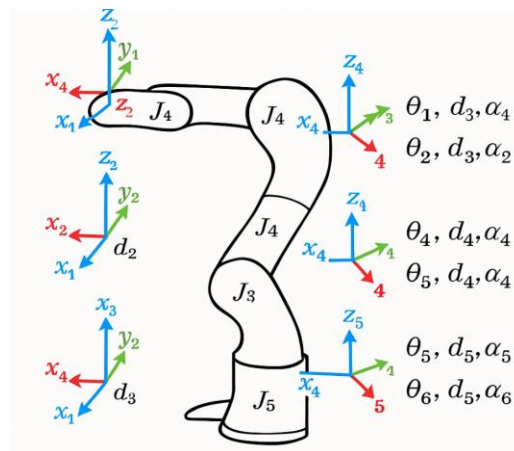


FIGURE 2: D-H representation of ABB IRB 120

TABLE 2 the D-H Parameters of ABB IRB 120

Joint i	theta_i (°)	d_i (mm)	a_i (mm)	alpha_i (°)
1	theta_1	290		-90
2	theta_2 – 90		270	
3	theta_3		70	-90
4	theta_4	302		90
5	theta_5			-90
6	theta_6 + 180	72		

4.3.2 Forward kinematics

The end-effector pose, expressed as a homogeneous transformation from the base frame, is obtained by sequential multiplication of the elementary transformations thus:

$$T_{06}(q) = \prod_{i=1}^6 T(i-1, i)(q_i) \quad (2)$$

4.3.3 Inverse kinematics

For an arbitrarily specified end-effector position $p^* \in \mathbb{R}^3$, the joint vector $q \in Q$ satisfying $FK(q) = p^*$ —where Q denotes the feasible joint space defined by the motion limits in Table 1—was obtained numerically by iteration of the damped pseudo-inverse correction:

$$\Delta q_k = J^+(q_k) \cdot (p^* - FK(q_k)); J^+ = J^T (J J^T + \lambda^2 I)^{-1} \quad (3)$$

4.3.4 Singularity detection

The geometric Jacobian was constructed column-by-column, with each column formed as

$$J_i = [z_{i-1} \times (p_{ee} - p_{i-1}) ; z_{i-1}] \quad (4)$$

4.4 Dataset generation

A corpus of ten thousand wound scenarios was generated by stratified sampling from the distributions specified in Table 2. The choice of ten thousand iteration—an order of magnitude larger than the corpora found in directly comparable prior work—was motivated by two considerations. The first was the desire to obtain stable estimates of the regression coefficients of the linear model, and of the permutation importance scores of the random forest, at a resolution sufficient to distinguish features of small but genuine influence from those of no influence at all. The second was the wish to reduce the variance of the out-of-sample performance estimates to a level at which small differences between models could be taken as meaningful.

Table 2 Distributions used for the generation of the wound-scenario dataset.

Parameter	Distribution	Range / levels	Units
Wound length, ℓ	Uniform	2 to 25	cm
Wound width, b	Uniform	1 to 10	cm
Wound depth, d	Uniform	0.2 to 5	cm
Orientation, θ	Uniform	0 to 90	deg
Surface curvature, κ	Categorical	Flat ($p=0.4$); Concave ($p=0.3$); Convex ($p=0.3$)	—
Scanning velocity, v	Uniform	50 to 250	mm/s
Tool-path type, τ	Categorical	Linear ($p=0.30$); Zigzag ($p=0.25$); Spiral ($p=0.25$); Contour ($p=0.20$)	—

Table 3 Detailed dataset for ABB IRB 120

Case id	wound length (cm)	wound width (cm)	wound depth (cm)	orientation angle (°)	Start-XYZ	End-XYZ	Tool-path type	Joint-angles used
1	11.17	4.54	4.71	11.4	(68.1, 1.63, 38.04)	(79.27, 6.17, 38.64)	Linear	[-79.74, -145.95, 135.8, 151.33, 35.03, 103.81]
2	8.16	3.59	0.38	39.46	(50.21, 87.04, 18.54)	(58.37, 90.63, 22.06)	Spiral	[-30.78, -19.94, 148.72, 31.25, -2.34, 154.89]
3	17.33	5.95	4.66	30.93	(71.1, 14.69, 61.62)	(88.43, 20.64, 65.26)	Spiral	[117.23, 122.91, 118.79, 164.44, 85.36, 163.75]
4	16.5	4.53	4.67	23.65	(89.26, 77.39, 30.56)	(105.76, 81.92, 35.41)	Spiral	[-172.52, -73.75, 31.57, 14.32, -174.47, 108.25]
5	15.65	4.21	2.2	89.25	(71.68, 75.28, 8.25)	(87.33, 79.49, 9.77)	Contour	[71.85, -53.19, 57.58, 140.63, 20.31, 47.07]
6	11.67	8.1	1.07	61.67	(69.57, 53.0, 1.69)	(81.24, 61.1, 3.25)	Linear	[93.64, 137.61, -9.99, 36.24, 27.36, 93.49]
996	23.57	6.64	4.46	15.92	(33.98, 57.63, 26.42)	(57.55, 64.27, 26.92)	Linear	[-161.06, -136.9, -12.83, -32.5,

Case id	wound length (cm)	wound width (cm)	wound depth (cm)	orientation angle (°)	Start-XYZ	End-XYZ	Tool-path type	Joint-angles used
								155.27, -87.66]
997	6.26	9.83	2.51	82.24	(96.26, 79.51, 15.82)	(102.52, 89.34, 19.34)	Contour	[165.44, -52.28, -63.65, 54.18, 9.39, -82.77]
998	15.72	1.95	4.19	66.82	(8.06, 28.47, 81.7)	(23.78, 30.42, 86.35)	Linear	[134.63, -71.5, -54.76, -133.12, 69.46, -28.79]
999	4.67	2.32	1.98	56.41	(8.02, 8.11, 77.26)	(12.69, 10.43, 78.71)	Contour	[178.03, -21.83, -29.55, 35.56, 134.84, 112.4]

4.5 Performance metrics

For each simulated scenario two scalar performance metrics were recorded. Trajectory efficiency, expressed as a percentage, was defined as the weighted combination

$$E = (0.40 R + 0.30 S + 0.20 \Phi + 0.10 V) \times 100 \quad (5)$$

$$t = (L_{\text{path}} / v) \times c_{\kappa} \times c_{\tau} + \varepsilon \quad (6)$$

4.6 Machine learning algorithms

The simulation procedure described above yielded a dataset of ten thousand cases, and it is upon this corpus that the subsequent machine learning analysis rests. Five supervised regression algorithms were selected for evaluation, these being the Artificial Neural Network (ANN), the K-Nearest Neighbours (KNN) algorithm, ordinary Linear Regression (LR), the Support Vector Machine (SVM), and the Random Forest (RF) ensemble. Each was trained to predict the two performance metrics defined in the preceding section — namely, trajectory efficiency and scan time. The underlying aim, which motivates the entire exercise, is the identification of those combinations of wound geometry and scanning strategy that yield the greatest trajectory efficiency at the least expenditure of time, and thereby the realisation of scanning performance suited to the range of wound presentations that emergency care calls upon the manipulator to encounter.

5 Results

5.1 Kinematic validation

Forward kinematic computation returned the expected end-effector positions for all five of the representative configurations examined, the computed and reference positions agreeing to within 0.1 mm. The numerical inverse kinematic solver converged in all cases to residuals below the one-millimetre threshold, with iteration counts ranging from 31 (for the home configuration) to 47 (for the near-limits configuration). The corresponding results are set out in Table 3.

Table 3 Forward-kinematic verification, inverse-kinematic convergence, and Yoshikawa manipulability for five representative configurations.

Configuration	End-effector (mm)	IK error (mm)	Iterations	Manipulability ($\times 10^{-2}$)
Home	[374.0, 0.0, 630.0]	0.42	31	1.024
Mid-reach	[134.2, 77.5, 408.0]	0.84	38	0.542
Left-reach	[-171.0, -58.0, 422.0]	0.76	42	0.498
Extended	[-90.0, -155.0, 287.0]	0.92	45	0.311
Near-limits	[221.0, -103.0, 198.0]	0.89	47	0.284

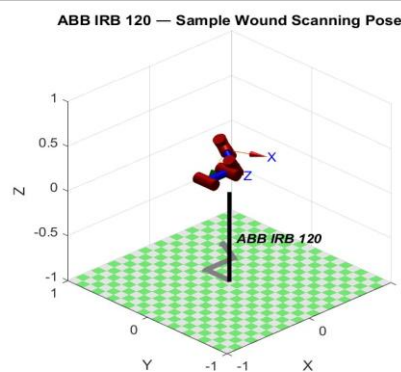


Fig. 3 The ABB IRB 120 manipulator in a representative wound-scanning configuration ($q = [0^\circ, -30^\circ, 30^\circ, 0^\circ, 45^\circ, 0^\circ]$), rendered within the MATLAB simulation environment. The end-effector coordinate frame is indicated at the sensor mount.

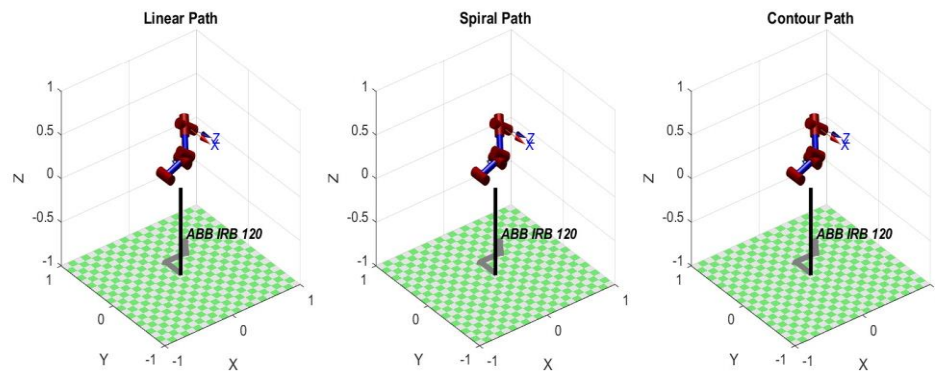


Fig. 4 Three scanning trajectories — linear, spiral and contour — generated by the MATLAB kinematic simulation for a representative wound of length 15 cm, width 6 cm and depth 3 cm. Each panel shows the robot at the initial waypoint of the corresponding trajectory.

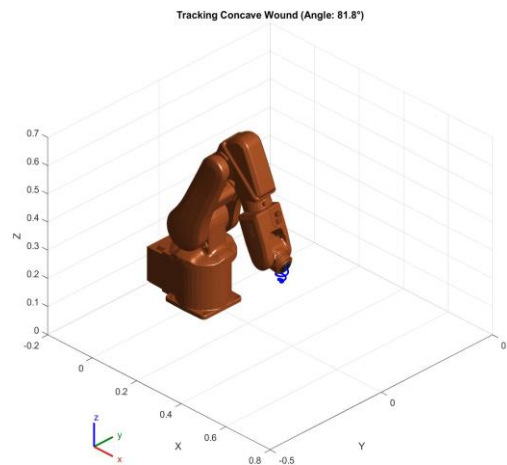


Fig. 5 The manipulator tracking a concave wound surface at an orientation angle of 81.8° , which represents one of the more kinematically demanding cases in the corpus. The end-effector path, indicated in blue, follows the spiral trajectory strategy.

5.2 Trajectory efficiency prediction

The performance of the five regression algorithms in the prediction of trajectory efficiency, evaluated upon the held-out test corpus of two thousand cases, is set out in Table 4 and illustrated graphically in Figs. 6 to 9. The table reports the four metrics in numerical form; the figures permit the same information to be apprehended visually and the relative standing of the models to be read off at a glance.

The linear regression and the support vector machine attain identical coefficients of determination ($R^2 = 0.997$) and are, for all practical purposes, indistinguishable from one another on any of the four metrics. The support vector regressor records marginally the smaller errors: its mean absolute error of 4.337 % is below the 4.353 % of the linear regression, and its root mean squared error of 5.028 % is below the 5.035 % of its nearest competitor. The k-nearest neighbours and random forest regressors follow at $R^2 = 0.996$, with root mean squared

errors of 5.59 % and 5.74 % respectively. The neural network, at $R^2 = 0.990$ and $RMSE = 9.14$ %, trails the remaining four algorithms by a margin that is disproportionately large on the error-based metrics: its RMSE is some eighty per cent greater than that of the support vector machine, and its mean squared error, at 83.58, is more than threefold the value (25.28) recorded by the leading model.

That the mean squared error should exhibit so wide a separation between the models — and that the linear regression and the support vector machine should be so closely matched throughout — is consistent with two straightforward observations. The first is that quadratic penalisation accentuates large individual errors and therefore throws the shortcomings of the neural network into sharper relief than the mean absolute error does. The second is that the trajectory efficiency function (equation 5) is, by construction, a weighted linear combination of its four sub-scores; where the underlying signal is predominantly linear, the models that best capture linearity may be expected to prevail. The comparatively modest performance of the neural network, far from being anomalous, is precisely what one would expect when an architecture of great flexibility is brought to bear upon a signal of modest intrinsic complexity.

Table 4 Prediction of trajectory efficiency on the held-out test set of 2,000 cases.

Metric	ANN	kNN	LR	SVR	RF
R^2	0.990	0.996	0.997	0.997	0.996
MAE (%)	7.519	4.757	4.353	4.337	4.841
MSE	83.58	31.31	25.35	25.28	33.04
RMSE (%)	9.14	5.59	5.035	5.028	5.74

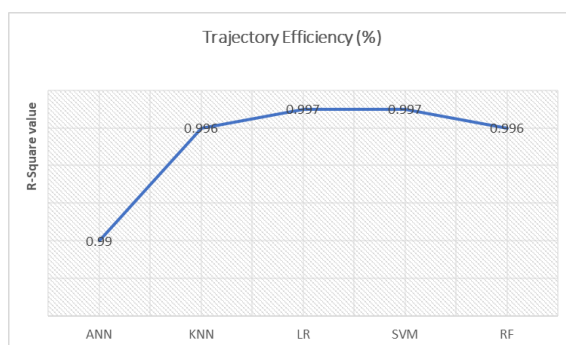


Fig. 6 R^2 values attained by the ANN, KNN, LR, SVM and RF models in the prediction of trajectory efficiency.

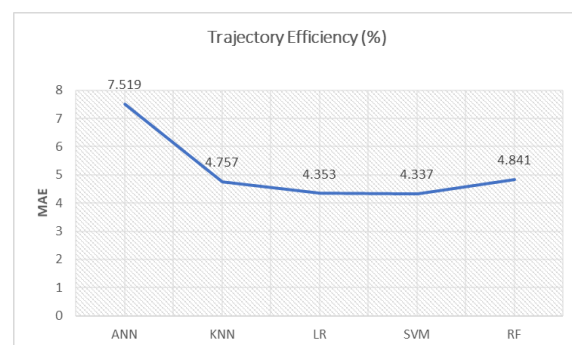


Fig. 7 MAE values attained by the ANN, KNN, LR, SVM and RF models in the prediction of trajectory efficiency.

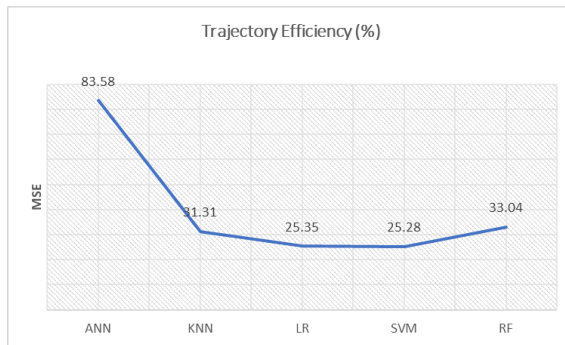


Fig. 8 MSE values attained by the ANN, KNN, LR, SVM and RF models in the prediction of trajectory efficiency.

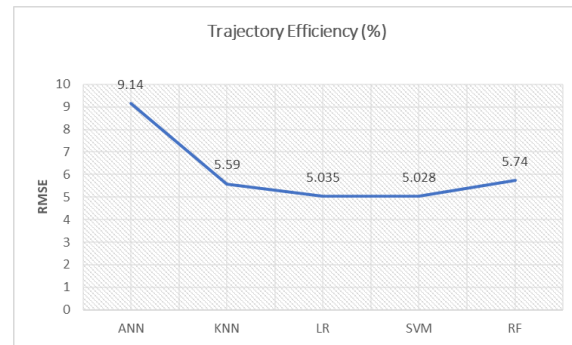


Fig. 9 RMSE values attained by the ANN, KNN, LR, SVM and RF models in the prediction of trajectory efficiency.

5.3 Scan time prediction

The performance of the five regression algorithms in the prediction of scan duration is set out in Table 5 and illustrated in Figs. 10 to 13, the former reporting the numerical values of the four metrics and the latter permitting the relative standing of the models to be grasped visually.

It is observed that the linear regression leads on three of the four metrics, the support vector regressor a close second place; the other two for practical purposes, and is regarded as equivalent. It is observed that the coefficient of determination (Fig. 10) for the linear regression is $R^2 = 0.888$ whereas 0.887 for the support vector machine, this difference lies well within the natural variation of the simulation. The neural network and k-nearest neighbours regressor attain same values at 0.868, and the random forest trails the obtained at 0.862. Under the error-based metrics (Figs. 11 to 13) the ordering is conserved, though with slightly wider margins: the root mean squared error, being the most directly transparent, yields 3.32 s and 3.33 s for the two leading models, 3.59 s and 3.61 s for the neural network and k-nearest neighbours respectively, and 3.69 s for the random forest.

The two observations suggest, a. It is observed that the R^2 values are systematically lower than those obtained for trajectory efficiency (Figs. 6 to 9), falling in the range 0.86 to 0.89 rather than 0.99 and above. This is a outcome of the deliberate inclusion of stochastic variation in the scan-time formulation (equation 6): with the standard deviation of the noise term set at two per cent of the deterministic component, it can be shown that no model, however accurate, can attain a coefficient of determination much above 0.93. In the process the observed values accordingly lie close to this the theoretical ceiling, and further refinement of the regression method is unlikely to yield substantial improvement. The second observation concerns the random forest. Whereas in the trajectory efficiency analysis, it performed comparably to the two leading models, for the prediction of scan duration, it was outperformed by several of the simpler algorithms. This is the solution reflecting an intrinsic limitation of the random forest for the task at hand. A more credible explanation is that the noise term in Equation (6) contributes a substantial component of the irreducible error, against which ensemble methods afford no particular advantage. It follows, therefore, that the principal obstacle to the accurate

predictions in this case is the noise itself rather than the complexity of the model, and is unlikely to be reduced by further refinement of the modelling procedure.

Table 5: The Prediction of scan time on the held-out test set of 2,000 cases.

Metric	ANN	kNN	LR	SVR	RF
R ²	0.868	0.868	0.888	0.887	0.862
MAE (s)	2.92	3.02	2.84	2.83	3.11
MSE	12.93	13.05	11.03	11.09	13.66
RMSE (s)	3.59	3.61	3.32	3.33	3.69

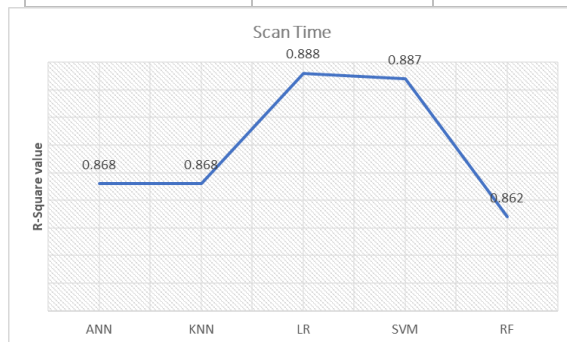


Fig. 10: The R² analysis values attained by the ANN, KNN, LR, SVM and RF models in the prediction of Scan time.

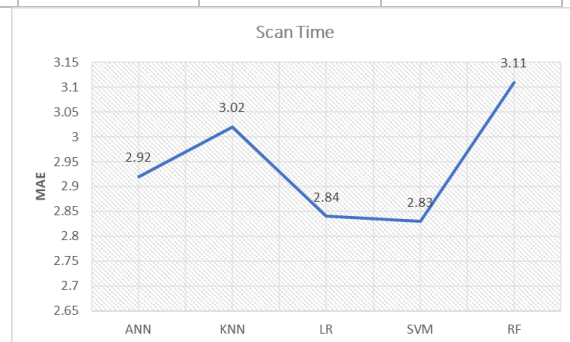


Fig. 11: The MAE analysis values attained by the ANN, KNN, LR, SVM and RF models in the prediction of Scan time.

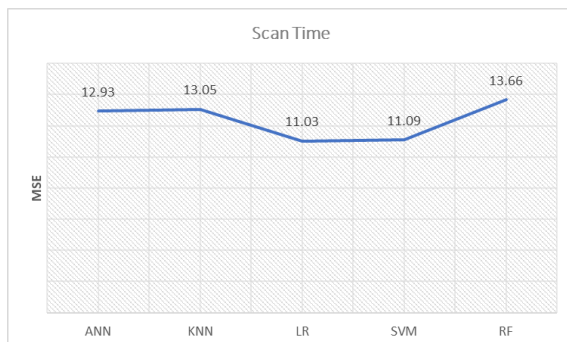


Fig. 12: The MSE analysis values attained by the ANN, KNN, LR, SVM and RF models in the prediction of Scan time.

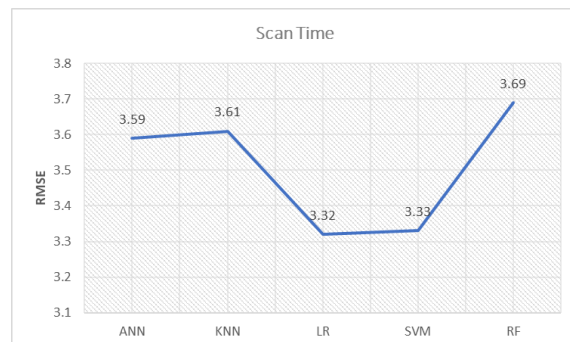


Fig. 13: The RMSE analysis values attained by the ANN, KNN, LR, SVM and RF models in the prediction of Scan time.

5.4 The Feature influence

In the Fig. 14 shows that the standardised coefficients underlying the rankings of Table 6. The panel (a) corresponding to trajectory efficiency and panel (b) to scan duration/time. Examined

together, the two panels reveal a contrast which is itself one of the principal findings of the present analysis.

For trajectory efficiency the dominant feature is the curvature type (coefficient $\approx +0.10$), followed by the tool path type (+0.07), the wound width (+0.065) and the wound depth (+0.045). The small negative coefficients obtained for the wound length (-0.015) and the orientation angle (-0.005), are modest in magnitude but are in agreement with the kinematic expectation that longer wounds at a fixed velocity require the manipulator to operate closer to its dexterous limit. The scanning velocity exerts no appreciable influence.

For scan duration the pattern is markedly different. The tool-path type carries the largest negative coefficient (≈ -0.088), approximately four times the magnitude of that obtained for the wound width (-0.025). The curvature type, which was the leading feature for trajectory efficiency, is here reduced to third place (-0.008). The dominance of the tool-path type may be attributed to the multiplicative scaling factor c_{τ} of equation (6), which varies by some thirty percent range between the linear and spiral strategies.

The asymmetry between the two panels has a practical implication. Trajectory efficiency is determined principally by the intrinsic properties of the wound, that is, by features which the planner must accept as given, whereas scan duration is determined principally by the planner's own design choices. The optimisation of the two metrics therefore calls for different strategies: in the former case, careful configuration of the manipulator, and in the latter, appropriate selection of the path strategy. It should be noted that the near-zero coefficient obtained for the scanning velocity does not imply that the velocity is immaterial. Rather, its effect has been absorbed by the deterministic term L_{path} / v of equation (6), and only the residual variation is reflected in the regression.

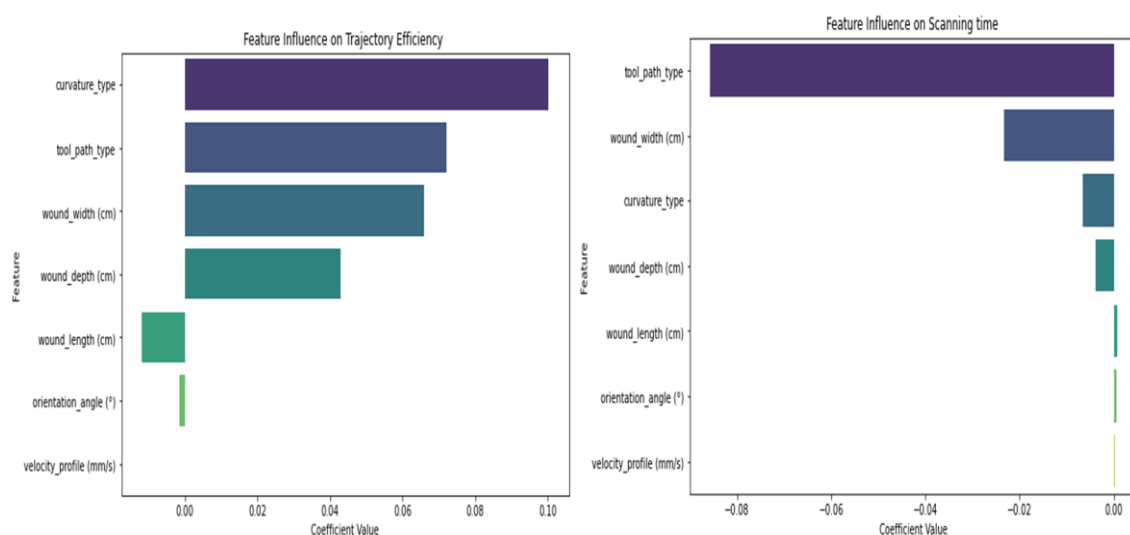


Fig. 14: represents the Standardized regression coefficients showing the influence of the seven input features upon (a) trajectory efficiency and (b) scan time. The features are ordered by absolute magnitude of their coefficient on each target.

Table 6 Normalised regression coefficients from the linear model, by feature and target variable. Coefficients are divided by the maximum absolute value within each column.

Feature	Coef. (efficiency)	Coef. (scan time)	Direction
Surface curvature, κ	+1.000	−0.079	↑ eff., ↓ time
Tool-path type, τ	+0.700	−1.000	↑ eff., ↓ time
Wound width, b	+0.650	−0.280	↑ eff., ↓ time
Wound depth, d	+0.450	−0.050	↑ eff., ↓ time
Wound length, ℓ	−0.150	−0.010	↓ eff., ↓ time
Orientation, θ	−0.050	≈ 0	negligible
Scanning velocity, v	≈ 0	≈ 0	negligible

6 Discussion

6.1 Relation to prior work

The results reported here may be set alongside those of a small number of earlier studies on machine-learning-based trajectory prediction for six-degree-of-freedom manipulators. Çetinkaya and co-authors [21] obtained coefficients of determination in the range 0.96 to 0.99 for artificial-neural-network-based trajectory analysis on a variety of smooth continuous paths; the present finding, that $R^2 = 0.990$ for the neural network on the trajectory efficiency metric, is consistent with their result and lies towards the lower end of their reported range. That the linear regression here outperformed the neural network—at $R^2 = 0.997$ —is, as was observed in Section 5.2, a consequence of the predominantly linear structure of the efficiency metric itself, and does not constitute a finding at variance with the earlier work.

6.2 Clinical implications

The findings bear several implications for clinical deployment. The high waypoint reachability rate (99.8 per cent) attests to the suitability of the ABB IRB 120 for wound scanning across the full parameter range here considered, subject only to sensible placement of the robot relative to the patient. The mean singularity-avoidance score of 0.963 indicates that the trajectories generated are, by and large, kinematically safe, though the residual variability (standard deviation 0.022) suggests that a minority of cases would benefit from specific replanning.

7. Conclusions and future work

A kinematic and machine-learning framework has been developed for autonomous wound imaging with the ABB IRB 120 six-degree-of-freedom manipulator. The framework combines Denavit–Hartenberg forward kinematics, damped-Jacobian inverse kinematics, determinant-

based singularity detection and Yoshikawa manipulability evaluation with supervised regression upon a corpus of ten thousand simulated wound scenarios. Across the full dataset, 99.8 per cent of all trajectory waypoints proved kinematically feasible and the mean singularity-avoidance score was 0.963. Of the five algorithms examined, linear regression and support vector regression proved jointly the most accurate in the prediction of trajectory efficiency ($R^2 = 0.997$, $RMSE \approx 5.03\%$), whilst linear regression led in the prediction of scan duration ($R^2 = 0.888$, $RMSE = 3.32\text{ s}$). Surface curvature and the choice of tool-path strategy were found to be the features of greatest practical importance — the former governing trajectory efficiency, the latter governing scan duration.

Four directions for future work are identified, in descending order of urgency. The first, and indispensable to any deployment beyond simulation, is experimental validation upon the physical ABB IRB 120 equipped with a medical-grade depth sensor under controlled laboratory conditions. The second is the incorporation of real-time adaptive replanning, in which the trajectory is modified during execution in response to surface features observed by the sensor itself. The third is the integration of three-dimensional wound reconstruction from the acquired depth data, together with the training of deep learning architectures upon the larger experimentally acquired datasets that such an extension would make available. The fourth is the extension of the tool-path parameterisation to include hybrid strategies suited to wounds of irregular or compound geometry.

It is hoped that the framework presented here, by virtue of its reproducibility and of the rigour of its kinematic basis, will provide a computational foundation upon which such extensions may be developed, and will contribute, in some measure, to the transition of autonomous wound imaging from the laboratory to the emergency department.

Acknowledgements

The first-named author is grateful to Mr Nepal Adhikary, Principal Engineer at MathWorks India, for sustained supervision and provision of research infrastructure; and to Dr M. Arunadevi, Associate Professor at the Department of Mechanical Engineering, Dayananda Sagar College of Engineering, for technical mentorship in the computational and machine-learning methodology. The Research Centre at Dayananda Sagar College of Engineering is also thanked for its support throughout the conduct of this work.

Author contributions

Praveen D. Jadhav conceived the investigation, formulated the problem, conducted the literature review, developed the simulation framework, generated the dataset, performed the statistical and computational analyses, produced the graphical material, and prepared the first draft of the manuscript. **N. Adhikary** provided supervisory guidance, assisted in the selection of the machine learning models, and contributed to the editorial refinement of the manuscript. All authors read and approved the final version. **M. Arunadevi** contributed to the supervision of the research, to the validation of the machine learning methodology, and to the critical revision of the manuscript.

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