PRLS-ASVM: A Hierarchical Calibration Framework Integrating RLS–PID Estimation and PIMO–SVM Compensation for Industrial Robots: Supplementary File

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This is the supplementary file for this paper. Additional tables and figures regarding the symbol appointment, model structure and experimental results are placed here.

I. Additional Tables

TABLE S.1
ABBREVIATIONS

Abbreviation	Meaning
PRLS-ASVM	Proportional Recursive Least Squares–Adaptive Support Vector Machine.
RLS-PID	Recursive Least Squares–Proportional Integral Derivative.
PIMO-SVM	Projection–Iterative–Methods–based Optimizer–Support Vector Machine.
RLS	Recursive Least Squares.
PID	Proportional Integral Derivative.
PIMO	Projection-Iterative-Methods-based Optimizer.
SVM	Support Vector Machine.
DH	Denavit-Hartenberg.
F-SVM	Feature-SVM.
LSSVR	Least-Squares Support Vector Regression.
RMSE	Root Mean Square Error.
STD	Standard Deviation.
MAX	MAXimum error.
RBF	Radial Basis Function.
EKF	Extended Kalman Filter.
DE	Differential Evolution.
PSO	Particle Swarm Optimization.
LM	Levenberg-Marquardt.
RGP	Residual Guided Projection.
DRP	Dual Random Projection.
WRPU	Weighted Random Projection Update.
LFGP	Lévy Flight Guided Projection.
GPU	Graphics Processing Unit.

TABLE S.2
NOMENCLATURE (ALL ABBREVIATIONS ARE DEFINED IN TABLE S.1)

Symbol	Explanation
X_0	Nominal DH parameters.
M	DH transformation matrix.
α / a / d / θ	Link twist angle / Link length / Link offset / Joint angle.
J	Jacobian matrix.
m	Number of sampling points.
L_i / L_i'	Measured / Theoretical cable length for the position i.
P_i / P_i'	Measured / Theoretical end-effector position.
P_0	Fixed reference point.
q_i	Joint rotation angle.
K_p / K_i / K_d	Proportional / Integral / Derivative gain parameter.
T_s	Sampling time.
ε	Regularization term.
P	Covariance matrix.
K	Gain vector.
X_{best1}	RLS-PID-optimized DH parameters.
X_{best2}	PIMO-SVM-optimized DH parameters.
X_{final}	PRLS-ASVM-optimized DH parameters.
K_n	RBF kernel function value.
$\bar{K}_n$	Mean kernel eigenvalue.
neti / *neto*	Hidden layer input / output.
S	Population of the PIMO algorithm.
N	Population size.
F	Population fitness array.
δ	Dynamic search intensity parameter.
γ	Adaptive random perturbation parameter.
R	Random weight coefficient.

TABLE S.3
ALGORITHM 1: PSEUDOCODE

Algorithm 1 RLS-PID		
Input: L_k, X_0		
Operation		**Cost**
01.	**initialize** $t = 0$ and T	$\Theta(1)$
02.	**initialize** $X = X_0$	$\Theta(1)$
03.	**initialize** K_p, K_i, K_d, T_s, P, λ	$\Theta(1)$
04.	**while not** converged **and** $t \leq T$ **do**	$\times\lvert T\rvert$
05.	| **for** $k = 1$ **to** m	$\times m$
06.	| | **set** q_k known	$\Theta(1)$
07.	| | Compute L_k' with Eq. (9)	$\Theta(1)$
08.	| | Compute J_k with Eq. (14)	$\Theta(1)$
09.	| | Compute e_k with Eq. (10)	$\Theta(1)$
10.	| | Compute $\tilde{e}_k$ with Eq. (11)	$\Theta(1)$
11.	| | Update K_k with Eq. (15)	$\Theta(1)$
12.	| | Update X_k with Eq. (16)	$\Theta(1)$
13.	| | Update P_k with Eq. (17)	$\Theta(1)$
14.	| **end for**	
15.	| $t = t + 1$	$\Theta(1)$
16.	**end while**	
Output: L_k', X_{best1}		

TABLE S.4
ALGORITHM 2: PSEUDOCODE

Algorithm 2 f_{SVM}		
Input: L_i, X_{best}, x		
Operation		**Cost**
01.	**initialize** $t = 0$ and $E_{max} = 0$	$\Theta(1)$
03.	**extract** $w = x[1{:}6]$, $w_0 = x[7{:}12]$	$\Theta(1)$
04.	**for** $i = 1$ to m	$\times m$
05.	| **set** q_i, $\bar{K}_{ni}$ known	$\Theta(1)$
06.	| Compute $\bar{K}_{ni}$ with Eq. (26)	$\Theta(1)$
07.	| **for** $h = 1$ **to** p	$\times p$
08.	| | Compute $neti_h$ with Eq. (28)	$\Theta(1)$
09.	| | Compute a_h with Eq. (29)	$\Theta(1)$
10.	| | Compute $neto_h$ with Eq. (30)	$\Theta(1)$
11.	| **end for**	
12.	| Compute Δq_i with Eq. (31)	$\Theta(1)$
13.	| Compute $\tilde{q}_i$ with Eq. (22)	$\Theta(1)$
14.	| Compute L_i' with Eq. (23)	$\Theta(1)$
15.	| Compute e_i with Eq. (20)	$\Theta(1)$
16.	| Update $E_{max} = \max(E_{max}, e_i)$	$\Theta(1)$
17.	**end for**	
Output: E_{max}		

TABLE S.5
ALGORITHM 3: PSEUDOCODE

Algorithm 3 PIMO-SVM

Input: L_i, X, N, $[lb, ub]$, dim, T

Operation		**Cost**
01.	**initialize** S with Eq. (33)	$\Theta(N\times dim)$
02.	**initialize** F	$\Theta(N)$
03.	**while** $t < T$ **to**	$\times T$
04.	| Update δ, γ with Eqs. (36) and (37)	$\Theta(dim)$
05.	| **for** $i = 1$ **to** N	$\times N$
06.	| | Compute $S_{n1}^{proj(t+1)}$ with Eq. (42)	$\Theta(dim)$
07.	| | Compute $F(x_i)$ with Eq. (34)	$\times m$
08.	| | Update S_{best}, F_{best} with Eq. (35)	$\Theta(1)$
09.	| | **if** $rand > rand$	
10.	| | | Compute $S_{n2}^{proj(t+1)}$ with Eqs. (44) and (45)	$\Theta(dim)$
11.	| | | Compute $F(x_i)$ with Eq. (34)	$\times m$
12.	| | | Update S_{best}, F_{best} with Eq. (35)	$\Theta(1)$
13.	| | **end if**	
14.	| | Compute $S_{n3}^{proj(t+1)}$ with Eqs. (47) and (48)	$\Theta(dim)$
15.	| | Compute $F(x_i)$ with Eq. (34)	$\times m$
16.	| | Update S_{best}, F_{best} with Eq. (35)	$\Theta(1)$
17.	| **end for**	
18.	| **if** $rand < O$ **then**	
19.	| | Compute $S_{n4}^{proj(t+1)}$ with Eq. (52)	$\Theta(N\times dim)$
20.	| | Compute $F(x_i)$ with Eq. (34)	$\times m$
21.	| | Update S_{best}, F_{best} with Eq. (35)	$\Theta(1)$
22.	| **end if**	
23.	**end while**	
24.	Compute X_{best2}	$\Theta(1)$

Output: X_{best2}

TABLE S.6
ALGORITHM 4: PSEUDOCODE

Algorithm 4 PRLS-ASVM

Input: L_i, X, N, $[lb, ub]$, dim, T

Operation	
01.	**initialize** $t = 0$ and Max-training-round = T
02.	**initialize** $X = X_0$, K_i, K_p, K_d, T_s
04.	**Execute** Algorithm 1
05.	Obtain X_{best1}
06.	**Construct** Algorithm 2 with X_{best1}
07.	**Execute** Algorithm 3
08.	Obtain $X_{final} = X_{best2}$

Output: X_{final}

TABLE S.7
TIME COMPLEXITY OF EACH ALGORITHM

Algorithm	**Computational Complexity**
M1	$\Theta(T_1\times m)$
M2	$\Theta(T_2\times m)$
M3	$\Theta(T_3\times m)$
M4	$\Theta(T_4\times m)$
M5	$\Theta(T_5\times m)$
M6	$\Theta(T_6\times m)$
M7	$\Theta(T_7\times m\times(k\times m))$
M8	$\Theta(T_8\times m)$
M9	$\Theta(N\times T_9\times m\times(k\times m))$
M10	$\Theta(T_8\times m+N\times T_9\times m\times(k\times m))$

TABLE S.8
TOTAL ITERATION TIME OF M1–M10 ON RMSE

Datasets	**Item**	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**	**M9**	**M10**
D1	Iteration	12	40	400	30	60	40	180	38	55	**65**
	Times(s)	493.34	2247.68	478.29	2722.96	2707.21	485.60	1225.40	568.20	582.50	**920.35**
D2	Iteration	13	40	400	30	60	32	145	35	50	**58**
	Times(s)	25.48	124.11	25.01	136.80	135.00	38.75	92.80	37.20	38.15	**62.48**
D3	Iteration	14	50	250	50	50	45	170	42	58	**68**
	Times(s)	70.35	220.77	116.89	438.11	221.09	108.40	228.55	138.65	145.80	**218.45**

TABLE S.9
COMPARISON OF NOMINAL AND PRLS-ASVM-CALIBRATED DH PARAMETERS
FOR ABB IRB120, HSR-JR680 AND UNIVERSAL10 ROBOTIC ARMS

Robot	**Joint *i***	**Initial structural parameters**				**Calibrated structural parameters**			
		a_i**(mm)**	d_i**(mm)**	α_i**(°)**	θ_i**(°)**	a_i**(mm)**	d_i**(mm)**	α_i**(°)**	θ_i**(°)**
ABB IRB 120	1	0	290	-90	0	0.030	289.877	-90.012	-0.004
	2	270	0	0	-90	269.881	0.013	0.000	-90.150
	3	70	0	-90	0	69.872	0.013	-90.011	0.572
	4	0	302	90	0	-0.121	302.014	90.012	0.161
	5	0	0	-90	0	-0.019	0.045	-90.011	0.575
	6	0	72	0	0	0.025	72.121	0.000	0.559
HSR-JR680	1	250	635.5	-90	0	250.484	636.263	-89.973	0.018
	2	900	0	0	-90	897.710	0.676	0.047	-89.920
	3	-205	0	90	180	-204.605	-0.162	90.018	179.996
	4	0	1030.2	-90	0	-0.501	1031.699	-89.947	0.020
	5	0	0	90	90	3.657	0.620	89.935	89.943
	6	0	200.6	0	0	-1.417	201.318	-0.176	-0.009
UNIVERSAL10	1	0	120	90	0	-1.965	119.657	90.079	-0.091
	2	-610	0	0	0	-609.930	2.287	0.050	0.037
	3	-570	0	0	0	-572.888	-1.509	-0.017	-0.022
	4	0	160	90	0	-1.347	159.455	90.083	0.051
	5	0	110	-90	0	1.982	110.538	-90.037	-0.131
	6	0	90	0	0	-3.161	89.802	-0.025	-0.007

TABLE S.10
WILCOXON SIGNED-RANK TEST ON RMSE/STD/MAX (DATA FROM TABLE 2)

Comparison	**R+**	**R-**	**p-value***
M10 vs. M1	45	0	0.0020
M10 vs. M2	45	0	0.0020
M10 vs. M3	45	0	0.0020
M10 vs. M4	45	0	0.0020
M10 vs. M5	45	0	0.0020
M10 vs. M6	45	0	0.0020
M10 vs. M7	45	0	0.0020
M10 vs. M8	45	0	0.0020
M10 vs. M9	45	0	0.0020

*The highlighted significance level of accepted hypotheses is 0.05.

II. Additional Figures

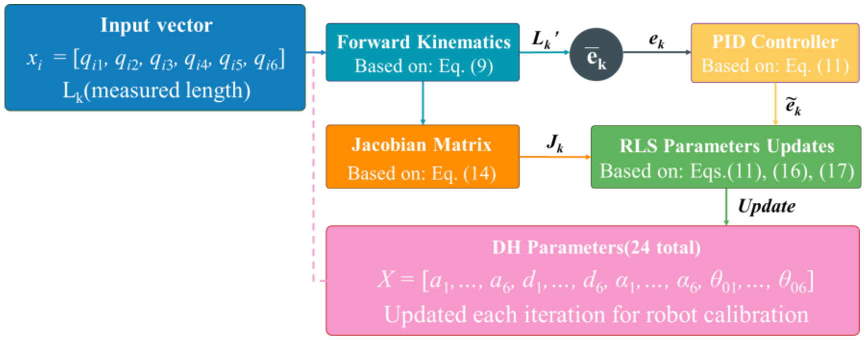

Fig. S.1. RLS-PID estimator for robot kinematic calibration.

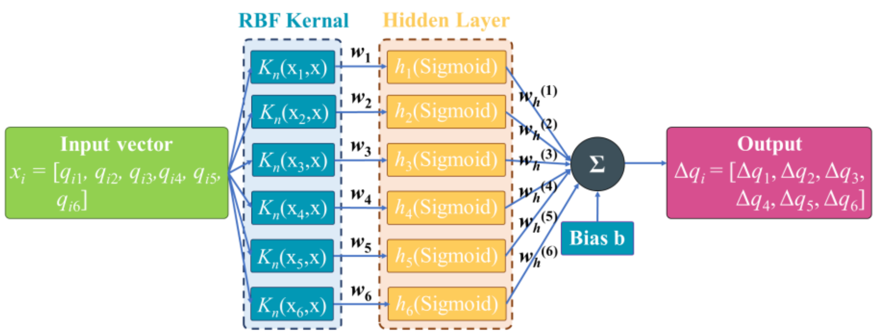

Fig. S.2. Layered neural network architecture inspired by SVM kernel methods.

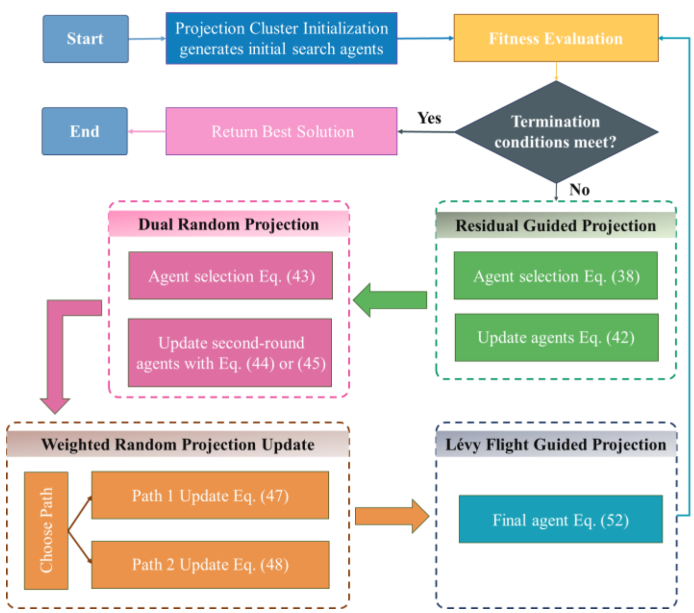

Fig. S.3. Flowchart of the PIMO algorithm.

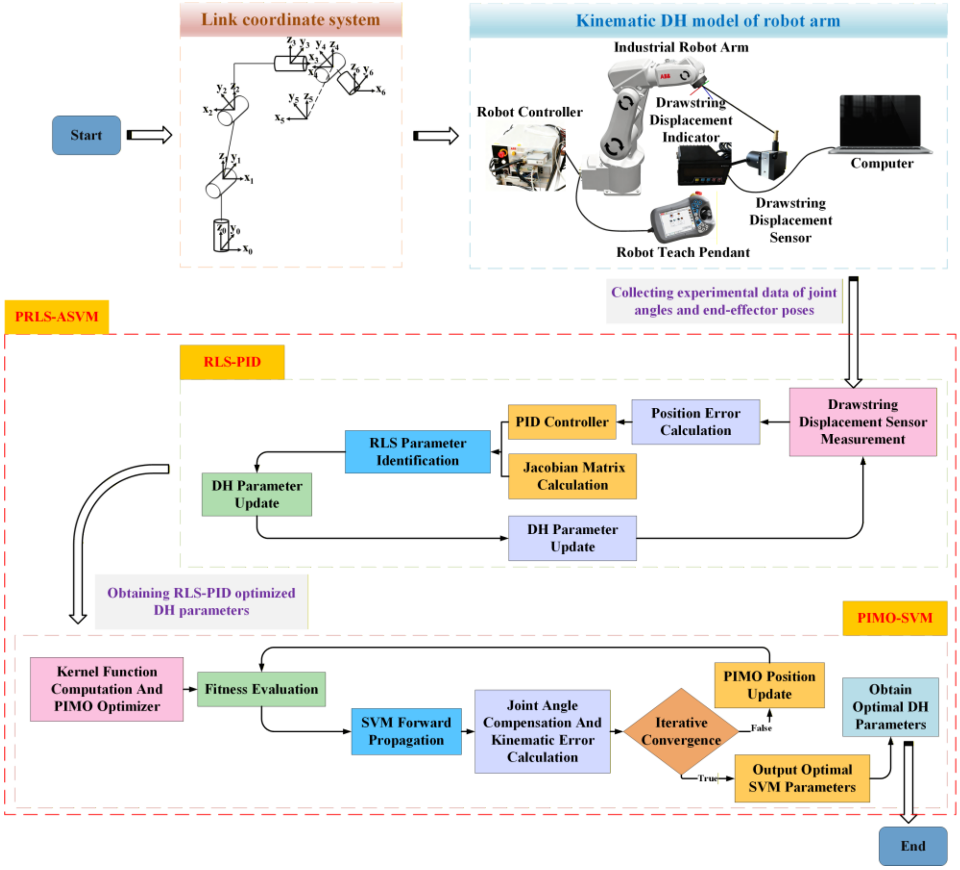

Fig. S.4. Cascaded Architecture Diagram of Proportional Recursive Least Squares and Adaptive Support Vector Machine (PRLS-ASVM).