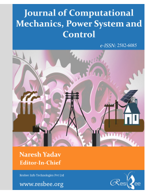
Vol.4 No.4 Oct 2021

Journal of Computational Mechanics, Power System and Control

Received 12 August, Revised 08 September, Accepted 14 October



Real-time Machine Learning Control for Robotic Manipulator by LNB: Lion Naïve Bayes Algorithm

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Abstract: A real-time Machine Learning Control (MLC) of articulated robotic manipulators is presented in this work by exploiting the Lion Optimization Algorithm (LOA) which is combined with the Naïve Bayes (LNB). Here, the proposed model is used for the real-time MLC of robotic manipulators by exploiting the "Fractional Order Proportional-Integral-Derivative (FOPID)" control scheme. Using the proposed LNB model MLC control gain parameters are tuned. By considering the dynamics of the actuator, to convene significant timing constraints, a "Real-Time Operating System (RTOS)" on a microprocessor collaborates with the LNB-MLC. At last, the Mechatronic design and investigational setup of a 6- degree of freedom (DOF) expressed robotic manipulator are modeled. The performance analysis is presented to show the advantage of the adopted models. While compared with the existing control models, the adopted optimization model has practice and theoretical consequences regarding online parameter tuning, real-time ability, and convergent behavior. In both industry and academia, the adopted MLC approaches are appropriate to design the real-time modern controllers.

Keywords: Control Models, FOPID, Machine Learning Control, Robot Manipulator, Real Time.

Nomenclature

Abbreviations	Descriptions
DOF	Degree of Freedom
GA	Genetic Algorithm
HRC	Human Robot Collaboration
ABC	Artificial Bee Colony
QPSO	quantum PSO
GSA	Gravitational Search Algorithm
D-H	Denavit-Hartenberg
DSP	digital signal processing
LOA	Lion Optimization algorithm
IK	Inverse Kinematics
PSO	Particle Swarm Optimization

1. Introduction

The robotic manipulators are able to perform the recurring tasks in a speedy manner, and with accuracies that function beyond the human operators. At present, robotic manipulator is an extensively exploited in manufacturing processes like painting and spot welding. In order to carry out the tasks reliably and accurately, manipulators' hand locations, as well as velocities, are digitally controlled [1]. By exploiting a separate position control system, each DOF or motion of the manipulator is located. By a supervisory computer, all the motions are coordinated to attain the preferred speed and placing of the end effectors. Additionally, the computer presents an interface between the operator and robot which permits programming the lower-level controllers and undeviating their actions [8]. From the supervisory computer, the control methods are downloaded to the control computers which are usually specialized microprocessors called DSP chips [18].

The utilization of techniques for the robot's representation embodiment and their communication with the environment is widespread in the intelligent robotics field for action prediction and control.

https://doi.org/10.46253/jcmps.v4i4.a3

Techniques can result systematically on the basis of the physics and robot structure. Nevertheless, such techniques cannot manage changes in the robot structure and dynamic environments [17]. Moreover, analytical computation of models, particularly on low-cost manipulators with elastic actuators, is too complicated or not possible [9].

To surmount such issues towards the improvement of adaptive and cognitive robots, techniques must b a substitute as learned online by exploiting sensory data streams. In general, model learning can be described as a procedure wherein an agent can deduce the distinctiveness of its structure and environment. Therefore, data-based model learning techniques have turned out to be well-liked for being capable of precisely modeling complex robotic systems. Here, many of the conventional approaches can be categorized into 3 classifications as Indirect Modeling, Direct Modeling, and Distal Teacher Learning [10].

Nowadays, industrial robots encounter numerous confronts [4]. Numerous times, robots require to be capable with a few degrees of self-sufficiency to acclimatize their behavior to the environment state and other agents. For instance, it is the scenario of HRC applications, wherein the robot has to consider the operator attendance to evade/edge collisions, minimize interference, and maximize the process throughput. HRC needs a modification of paradigm regarding standard industrial robot applications such as human-robot communication has to be taken into account at diverse levels such as planning, safety, control, sociology, scheduling,) and an incorporated technique is essential to organize an effectual HRC model. Amid all the aforesaid features, it is evident that a basic need for such dynamic applications has the capability of the robot to modify its motion at runtime. Like this capability, it is very important to permit the robot to act in response instantly to the present state of other agents for instance humans as well as other robots. The security of the communication is directly affected, however, it increases the throughput, as an optimized motion re-planning may minimize or evade robot halts and excessively conventional slowdowns. In two diverse manners, the online enhancement of the robot motion is carried out. They are by enhancing only the velocity profile while keeping the original path, or by enhancing the complete trajectory that the robot needs to pursue. Generally, the initial choice is very complicated as it needs to run the path planning approaches and verify the collision at run time. The subsequent choice is frequently favored due to its only need to slow down the trajectory execution beside with a similar path. Hence, it does not need to formulate a novel collision-free path and it is smaller from the computational perspective [11].

In the last decades, many studies have been conducted regarding diverse meta-heuristics approaches to resolve inverse kinematic issues. In [1], "a performance analysis of a 4 DOF robotic manipulator" by exploiting the PSO algorithm, GSA, GA, and quantum PSO QPSO algorithm was developed. In [2], a variant of ABC to resolve IK issue of a 5 DOF manipulator was presented. The diverse variants of PSO for an IK issue of a 7 DOF manipulator were presented in [3]. In [4], a QPSO-based model was developed to resolve the IK issue of a seven DOF manipulator. In [6], a GSA-based model was developed to attain solutions to the IK issue of a 7 DOF robot manipulator. Moreover, numerous studies for diverse optimization approaches exploited for IK analysis for diverse robotic manipulators were presented in [5]. Aforesaid studies have enthused the adopted model work to pursue the example of an optimization model to resolve IK issue of an extensively well-liked seven DOF robotic manipulator. Nowadays, deep learning approaches are well-known, Machine learning practitioners have gazed into robotics as the subsequent frontiers of confrontation. Simultaneously, robotics has developed ML machinery into their conventional workflows. Because of the requirement to carry out continued mechanical work on the globe, robotics issues break the independent and identical distribution supposition of the supervised learning example. These issues have motivated novel techniques, both from ML and classical model-based viewpoints.

2. A Mathematical Formulation of Robotic Manipulators

The Euler-Lagrange formulations of an n -link rigid robotic manipulator is stated as below:

$$D(p)\ddot{p} + E(p,\dot{p})\dot{p} + g(p) = u(t) \tag{1}$$

where $u(t)$ indicates the control input, $p \in R^n$ indicates the vectors of joint position, $\dot{p} \in R^n$ indicates the velocity, $D(p)$ indicates bounded positive-definite inertia matrix; and $\ddot{p} \in R^n$, indicates acceleration, respectively that is applied torque on joints; $E(p,\dot{p})$ indicates "centripetal Coriolis matrix, and $g(p)$ represents gravity vector". An n -link rigid robotic manipulator dynamical model is stated as follows:

$$D(p)\ddot{p} + E(p,\dot{p})\dot{p} + F_d\dot{p} + F_s(\dot{p}) + \tau_d(p,\dot{p}) + g(p) = u(t) \tag{2}$$

Where, $\tau_d(p,\dot{p})$ indicates external disturbance, $F_d\dot{p} \in R^{n\times n}$ indicates dynamic friction coefficient matrix and $F_s(\dot{p}) \in R^n$ indicates static friction vector. Eq. (2) is reformulated as

$$D(p)\ddot{p} + n(p,\dot{p}) + F_d\dot{p} + F_s(\dot{p}) + \tau_d(p,\dot{p}) = u(t) \tag{3}$$

where $n(p,\dot{p}) = E(p,\dot{p})\dot{p} + g(p)$. From Eq. (3), one can find

$$\ddot{p} = -D_0(p)^{-1}\{n_0(p,\dot{p}) + F_d\dot{p} + F_s(\dot{p}) + \tau_d(p,\dot{p}) + \Delta D(p)\ddot{p} + \Delta n(p,\dot{p}) - u(t)\} \tag{4}$$

where $D(p) = D_0(p) + \Delta D(p)$ being the unknown and known parts of $D(p)$, correspondingly. $n(p,\dot{p}) = n_0(p,\dot{p}) + \Delta n(p,\dot{p})$ with $N_0(p,\dot{p})$ and $\Delta n(p,\dot{p})$ indicates unknown and known parts of $n(p,\dot{p})$, correspondingly.

2.1 Flight Systems, Robotics, and Vehicle Dynamics

From Eq. (4) n-link rigid robotic manipulator simplified model is attained as

$$\ddot{p} = f_0(p,\dot{p}) + D_0(p^{-1})u(t) + G(t) \tag{5}$$

where $G(t) = -D_0(p)^{-1}\{F_d\dot{p} + F_s(\dot{p}) + \tau_d(p,\dot{p}) + \Delta D(p)\ddot{p} + \Delta n(p,\dot{p})\}$ represents the lumped perturbations term and $f_0(p,\dot{p}) = -D_0(p)^{-1}n_0(p,\dot{p})$ represents bounded known nonlinear function.19

A FOPID controller is an expansion of a traditional PID controller by including a differentiator of order μ as well as an integrator of order λ named *PIλDμ* control. The generalized transfer function of FOPID control law by exploiting the fractional calculus is explained below [7]:

$$T_c(s) = \frac{U(s)}{I(s)} = K_P + \frac{K_i}{s^{\lambda}} + K_{D^{S^{\mu}}}, (\lambda,\mu \geq 0) \tag{6}$$

where $T_c(s)$ indicates transfer function. $I(s)$ indicate input signals and $U(s)$ indicates output signals in Laplace space, correspondingly. K_P indicate proportional gain, K_i indicates integration gain, K_d indicates derivative gain in FOPID control. The fuzzy theory is used to "present a real-time FOPID controller with auto-tuning ability, to adjust the control parameters at each sampling point and meet time constraints".

2.2 Robotic Manipulators for Real-Time MLC

A Lion Naïve Bayes Algorithm is developed for real-time MLC for 6-DOF articulated robot manipulators, which is described in this section. By exploiting the D-H convention, forward kinematics is derived. The IK is exploited by means of reverse coordinates techniques with the forward kinematic formulations. After the analysis of kinematics, the motion planning as well as dynamic plant model is used to model a Lion Naive Bayes robot arm MLC controller with accomplishment [7].

To form a kinematic chain articulated robotic arm comprises a link set that is linked by joints. To derive the forward kinematic formulations, the D-H convention is used for the 6-DOF robot manipulator. For robotic manipulators, on the basis of the traditional D-H convention, "D-H matrix A_i from coordinate $i-1$ to coordinate" i is stated as below:

$$^{i-1}A_i = rot_{z,\theta_i}, trans_{z,d_i}, trans_{x,a_i}, rot_{x,\alpha_i} \tag{7}$$

wherein *trans* indicates a transformation matrix, *rot* indicates a rotation matrix. The 4 quantities: d_i indicates joint distance, θ_i indicates joint angle, a_i states the link length as well as "twist angle are D-H parameters connected with link i as well as joint i of the 6-DOF articulated manipulator".

3. Proposed Model

LOA [13] conserves the considerable and real performance it generates the best solutions at a similar time. The LOA is on the basis of the social behaviors of the Lion. It ascertains optimal solutions based upon 2 behaviors of Lion called territorial takeover as well as territorial defense and disperses elderly solutions.

From solutions, Y^M, Y^F, and Y_l^N are generated in Pride Generation that indicates the pride generation of nomadic lions and female, male, correspondingly. For each data, the mean and variance are computed. As a solution vector, mean as well as the variance is indicated, which is assigned to Y^M, Y^F, and Y_l^N. Y^M, Y^F, and Y_l^N elements are indicated as $Y^M(k), Y^F(k)$, and $Y_l^N(k)$ in that, $k = 1, 2, \ldots, K$. Here, elements are represented as random integers that are generated within the bounds of minimum as well as maximum limits. "The number of kernel models to be optimized in indicated as K". The fertility of territorial female lions and male lions is calculated.

Initially, H_r indicated as Laggardness rate is set to "0". Subsequently H_r is raised, if reference fitness $\left(f^e\right)$ is higher than or equivalent to male lion fitness. Or else, H_r is reset, if the reference fitness is lesser than the male lion fitness, and the mail lion fitness is indicated as the reference fitness.

At first, I_r indicates sterility rate is set to "0" and ensures the easiness to discover if it goes beyond the utmost limit I_r^{max}. The utmost limit of I_r is set as "4" for the female lion oestrus period. h_c indicates a number of female generations and b_c indicates a number of female updates, which is set to "0". After that, a female lion is updated and h_c is increased by "1". If updated female lion fitness is lesser than female lion fitness, subsequently b_c is set to "1" and the updated female lion is an optimal female lion. Subsequently, I_r is augmented. This procedure is continued till female generation number h_c attains h_c^{max}. The utmost value of h_c is "10".

By exploiting eq. (8), (9), and (10), a female lion can be updated, wherein, y_s^{F+} indicates s^{th} vector element of Y^{F+} and y_k^{F+} indicates k^{th} updated female lion vector element Y^{F+}. s indicates arbitrary integer produced within the interval $[1,K]$, l_1 and l_2 indicates random integers produced within the interval $[0,1]$, and ∇ indicates female update function.

$$y_k^{F+} = \begin{cases} y_s^{F+} & ;\text{if } k = s \\ y_k^{F} & ;\text{otherwise} \end{cases} \tag{8}$$

$$y_s^{F+} = \min\left[y_s^{max}, \max\left(y_s^{min}, \nabla_s\right)\right] \tag{9}$$

$$\nabla_s = \left[z_s^F + \left(0.1l_2 - 0.05\right)\left(y_s^M - l_1 y_s^F\right)\right] \tag{10}$$

Mating comprises 2 steps such as mutation and crossover. 4 cubs are exploited with arbitrary crossover probability J_r on basis of natural littering rate [12] in the crossover operator. The crossover operation is indicated as eq. (11), wherein, E signifies length K crossover mask in that "0s and 1s" are arbitrarily filled on the basis of the J_r. $\circ$ indicates schur product or Hadamard product. $\overline{E}$ indicates one's complement of E. From crossover, function obtains $Y^c(q)$ which is q^{th} cub. Subsequently, by mutation, attains cubs Y^c are forced to experience "mutation with mutation probability" O_r. Hence, an equivalent number of new cubs Y^{N-c} is produced. Subsequently, by crossover, cubs Y^c attained by mutation, cubs Y^{N-c} attained that are positioned in a cub pool. Using the gender clustering [13] approach, one female and male cub is taken from cub pool along with the physical lion's nature [14]. The male cub represents primary optimal fitness and the cub that has second optimal fitness is selected as the female cub. The cub's age Y_c is set as "0" once female and male cubs are chosen.

$$Y^c(q) = E_q \circ Y^M + \overline{E}_q \circ Y^F ;q = 1,2,... \tag{11}$$

At a rate of Q_r, female cubs $\left(Y^{G-c}\right)$, as well as male cubs, $\left(Y^{B-c}\right)$ are forced to experience uniform arbitrary mutation. By mutated male cubs, old female cubs and male cubs are replaced as well as mutated female cubs correspondingly, if mutated female and mutated male cubs are superior to old female and male cubs. Y_c is increased by "1" and the Q_r is diverse from mutation probability O_r cub growth function at every iteration.

In the lion approach, the most important operator is the Territorial defense [19] which is exploited to guide the approach to carry out searching in an extensive way. By making survival fight, "nomad lions coalition, updating of pride and nomad coalition the territorial defense is performed". Here, based on H_r initializing nomadic lion $Y_2{}^N$ while H_r is lesser than or equivalent to the H_r^{max} initialize $Y_2{}^N$ by mutation with a mutation rate $1-Q_r$. Subsequently, in the nomadic coalition, a survival fight is carried out among the one lion as well as the lion in the pride. The Y^{t-N} represents winning nomadic lion resides in the territorial defense on the basis of winner take all technique [15]. The survival fight outcomes are supported to Y^{t-N} while subsequent criteria are met. Subsequently, by replacing male lion, pride is updated by winning nomadic lion. Likewise, if a nomadic lion is beaten, a nomadic coalition can be updated.

$$f\left(Y^{t-N}\right) < f\left(Y^M\right) \tag{12}$$

$$f\left(Y^{t-N}\right) < f\left(Y^{B-c}\right) \tag{13}$$

$$f\left(Y^{t-N}\right) < f\left(Y^{G-c}\right) \tag{14}$$

The nomadic lion is the subsequent process is coalition updating, in that nomadic lion Y^N is chosen if the H^N is higher than or equivalent to the unity exponential value. H_1^N is computed as below:

$$H_1^N = \exp\left[\frac{u_1}{\max(u_1, u_2)}\right] \frac{\max\left(f\left(Y_1^N\right), f\left(Y_2^N\right)\right)}{f\left(Y_1^N\right)} \tag{15}$$

wherein, u_1 indicates Euclidean distance amid Y^M and $Z_2{}^N$; u_2 indicates Euclidean distance amid Y^M and $Y_2{}^N$. Subsequently, male lion Y^M and male lion frequency $f\left(Y^M\right)$ are saved; if the consequence of defense is "0" as well as process is continual from fertility estimate step.

If the cubage is higher than or equivalent to utmost age, territorial takeover step is preceded or else territorial defense and cub growth function are iterated. The utmost age is set as "3". Territorial takeover is a procedure to provide an area to female cub as well as male cub after they become matured. If female cub is superior to female lion, subsequently female cub engages the female lion's location and I_r is set to "0" in the territorial takeover procedure.

There are 2 termination criteria's represented in eq. 16 and 17, wherein, R_F signifies number of function evaluations, E_T signifies target error, and R_F^{max} signifies a maximum number of function evaluations.

$$g\left(Z^M\right) \le E_T \tag{16}$$

$$R_F > R_F^{max} \tag{17}$$

In this paper, the enhanced Naive bayes classifier is developed. Naive bayes classifier [16] is described as a probabilistic classifier that is on the basis of the Bayes theorem as well as naive independent assumptions amongst features. Even though Naive bayes classifier is scalable as well as speedy and scalable, for all the probability models it does not appropriate. Hence, to generate the optimal probabilistic measures, the LOA is combined with Naive bayes classifier. For each sample, Naive bayes classifier discovers the variance and mean and "identifies posterior function. Ultimately, it returns sample which has high probability value as outcome".

4. Result and Analysis

In this section, experimentation analysis of adopted and conventional models such as GA, ABC, and PSO algorithms was demonstrated. As demonstrated in Fig. 1, adopted model converges to optimum solution rapidly as well as evolved solution is superior ones attained by ABC, GA and PSO approaches.

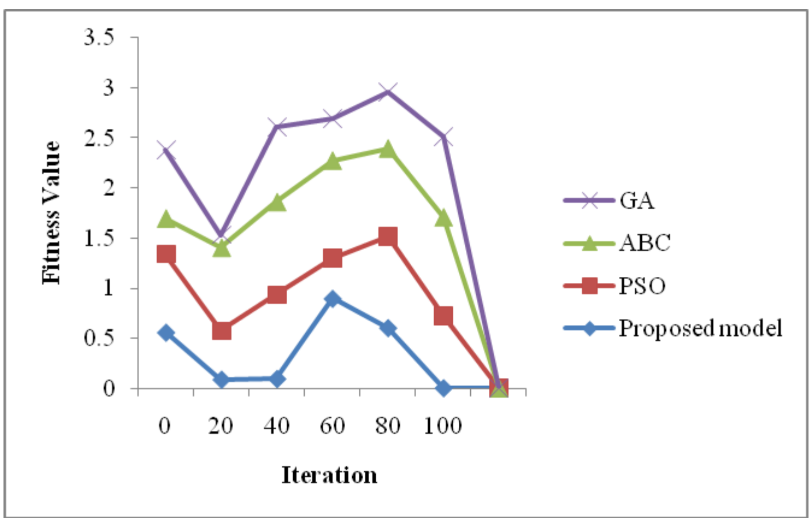

Fig. 1. *Convergence analysis of the proposed model*

5. Conclusion

A real time MLC of articulated robotic manipulators was presented in this work by exploiting LNB i.e., LOA with Naïve Bayes. To "real-time MLC of robotic manipulators", this hybrid optimization approach was exploited by involving FOPID control scheme. To convene the critical timing constraint, the MLC parameters were online tuned using Naïve Bayes based optimization algorithm. Finally, the simulation analysis was demonstrated to exhibit the developed MLV approaches over the conventional algorithms. The developed LNB-MLC has hypothetical and performs implication in both academic as well as industrial applications.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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