Integrating artificial immune systems and multi-layer perceptron-biogeography-based optimization for enhanced inverse kinematics in robotic arm

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ABSTRACT

Determining required joint angles to achieve a desired position in a manipulator's arm is a complicated problem without simple analytical solutions. This paper researches several computational methods based on artificial intelligence (AI) for calculating the joint positions of the 6-DOF robotic arm. We can extrapolate relevance, for example, to the crucial role that robotic manipulator arms play in industrial and medical applications, where enhanced precision and movement efficiency may sharply boost performance and expand applicability. Here, we investigate the effectiveness of methods, such as the artificial immune system (AIS) and multi-layer perceptron-biogeography-based optimization (MLP-BBO). Those AI-driven methods have been applied to determine joint angles for reaching desired positions through simulations for the robotic arm. The results show that the AIS and MLP-BBO approach can handle the intrinsic complexities of the task, thus testifying to the practicability and dependability of these two methods in this application. From the findings in the study, it was indicated that AI-driven techniques can effectively answer the complex problem of the robotic manipulator arm in finding joint angles.

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1. INTRODUCTION

Inverse kinematics (IK) has made a marked advance in the field of robotics with the combination of many types of computational methodologies into the IK hurdle. The inverse kinematics is a very fundamental part of robotic motion planning which deals with being able to find the joint movements that result in an end-effector position of the robot [1]. Older techniques faced problems of redundancy and convergence in complex robotic systems. Early innovative research [1], [2] discussed fuzzy logic techniques as the first to pioneer the refinement of IK solutions and to enhance convergence in redundant robot workspaces. Accordingly, the approach laid down the bases for work that can be improved upon in the future. Building on these basics, Momani *et al*. [3] expanded the frontier by researching traditional and continuous genetic algorithms that offer much faster rates of convergence for the optimization of IK problems in 3-DOF robot arms. On the other hand, neural networks have been employed for IK resolution using Cartesian trajectories. Duka [4] used neural netwsorks for the IK resolution in 3-DOF robots. In this work, solutions were accurately created by 3-DOF robots using Cartesian trajectories. On the other hand, Takatani *et al*. [5] and Habibkhah and Mayorga [6] proposed a new neural network architecture specially designed for 3-DOF redundant robots. This experimental setup demonstrates a highly efficient way of learning because of hybridization and data-driven synthesis. Therefore, the learning performance is impressive. These efforts demonstrate a change in the application of computational methodologies with robotic kinematics, making a new era of effectiveness and preciseness in robot manipulations. Table 1 shows a summary of some of the pioneering research conducted in the field of robotics, focusing on advancements used to solve IK problems. Each entry lists leading work where researchers have applied varied computational methodologies to further IK solutions.

Table 1. Overview of computational methods in robotics

Method	Authors	Year
Fuzzy logic technique	Aggogeri *et al.* [2]	2015
Genetic algorithms (GA)	Momani *et al.* [3]	2016
Feed-forward neural network	Duka [4]	2014
Neural network structure	Takatani *et al.* [5]	2019
Non-conventional neural network and virtual vector function method	Habibkhah and Mayorga [6]	2021
Least squares (LS), Recursive least square (RLS), and Particle swarm optimization (PSO)	Batista *et al.* [7]	2020
Artificial neural networks (ANNs)	Santos *et al.* [8]	2022
Combination of genetic algorithms and neural networks	Khaleel [9]	2018
Particle swarm optimization (PSO)	Hassan *et al.* [10]	2022

This paper introduces novel approaches in the domain of IK for robotics, aiming to enhance the robustness and adaptability of robotic systems across various environments. These approaches mark another significant step forward in the field's evolution. Alongside established methodologies like fuzzy logic [2], innovative strategies based on PSO [7], [10] and ANN [8], [9] have emerged as promising avenues for enhancing IK resolution.

We propose the use of the artificial immune system, inspired by the human immune system's adaptive and learning capabilities, along with multi-layer perceptron-biogeography-based optimization (MLP-BBO). These methods provide a unique framework for optimizing IK solutions, marking another significant step forward in the evolution of the field. The objective of this study is to demonstrate the efficacy of these approaches in improving IK resolution, thus contributing to the ongoing advancements in robotic manipulations.

The contributions of this manuscript are as follows.

- Introduction of the artificial immune system: This novel approach for IK resolution leverages adaptive and learning capabilities to enhance performance.
- Development of the MLP-BBO framework: This combines neural networks with biogeography-based optimization, improving the robustness and adaptability of IK solutions.
- Comprehensive evaluation: The methods are evaluated on the 6-DOF Robot arm, demonstrating significant improvements in convergence speed, precision, and computational efficiency.

By addressing these novel aspects, this paper aims to set a new benchmark in the field of robotic inverse kinematics, offering practical solutions to existing challenges and paving the way for more advanced robotic applications [1]–[13].

The subsequent sections of the paper are structured as follows: the second section presents the PUMA 560 robot arm. The third and fourth sections delve into the artificial immune system (AIS) and multi-layer perceptron (MLP) trained by BBO, respectively, elucidating their application in this study. The fifth section showcases computational results derived from the proposed methodologies, providing insights into their efficacy and performance. Finally, the paper concludes by summarizing conclusions and future perspectives, outlining key findings, and suggesting potential avenues for further exploration and development.

2. PUMA 560 ROBOT ARM

A robotic system works as a closed-loop, with its components (mechanical, electronics, and computer algorithms) working with each other to collect and run commands again and again. First, the robot's computer interprets information collected from the environment through sensors. Then, dedicated methods use the collected data to control commands to be sent to motors [14]. These commands then instruct the mechanical components to carry out the tasks. Continuous monitoring during operations is essential to correct any movement errors and ensure tasks are performed accurately.

In robotics, the range of motion of a manipulator arm is known as its workspace. The manipulator arm is typically mounted on a fixed base, which can be the floor, ceiling, or a special platform such as an operating table. It is a series of joints and links connected to a base. The end-effector, located at the final link as shown in Figure 1, is the tool that the robot uses when performing tasks [15]. Depending on the application, this end-effector could be a needle, grasper, scalpel, or another implement.

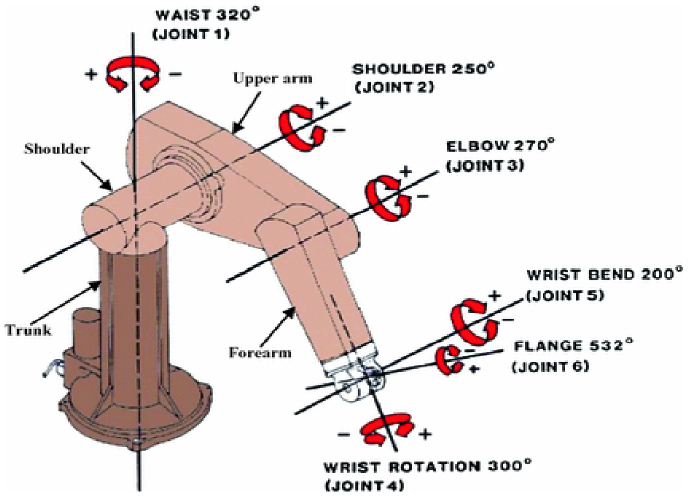

Figure 1. PUMA560 arm

In this paper, we focus on the PUMA560 [16] model, shown in Figure 1, a robotic arm with six joint angles labeled Q_1, Q_2, Q_3, ..., Q_6. Our main goal is to determine these angles to reach a target position in Cartesian space. Below we give a simplified mathematical process used to solve this problem.
Input: Target position (M)
Output: Joint angle parameters (Q)
Procedure:
– Define Q as the vector of model parameters: $Q = (Q_1, Q_2, Q_3, ..., Q_6)$.
– Solve for Q such that $f(Q) - M = 0$.

The solution requires optimizing norm $\|f(Q) - M\|$, which lands up the end-effector in the desired position. This must be with accurate precision. This process is crucial to the PUMA560 robot and any other robot, enabling them to perform its tasks accurately and effectively.

3. ARTIFICIAL IMMUNE SYSTEM

The AIS is a computational model inspired by the complexity of mammalian immune systems. This interdisciplinary field, often called computational immunology, is rapidly growing. AIS provides immunologists with a powerful tool for exploratory, experimental, and predictive tasks that are cumbersome or impractical with traditional laboratory methods.

The main purpose of AIS is to develop computational systems that mimic various functions of mammalian immune systems, which protect the body against foreign antigens by distinguishing two entities: self and non-self. These systems lend a hand to researchers gain new insights into complex immunological phenomena that might be difficult to interpret otherwise [17]. Enclosed by AIS, numerous methods have been developed to model different mammalian immune function sides. Notable examples include the three main concepts of immune function: negative selection, immune network, and clonal selection were discussed in [18].

Understanding the complex processes of the human immune system exposes a sophisticated connection among many types of immunity. We address how these ideas affect our computational approaches in the section that follows on the significant variations and links among innate immunity, adaptive immunity, and clonal selection. Like a microbiologist, innate immunity, also known as non-specific immunity, is the primary defensive mechanism the body uses against outside intruders. Natural and present from birth, this immune response provides general defense against many different illnesses and antigens [17].

A fundamental part of the immune system, adaptive immunity also known as acquired or particular immunity can identify and destroy certain foreign pathogens and chemicals, such as antibodies. Unlike natural immunity, adaptive immunity develops over time by exposure to antigens, therefore producing a tailored defense mechanism against particular threats [17], [19]. It is interesting that acquired immunity does not operate alone but rather together with natural immunity to efficiently identify and destroy foreign invaders, hence stressing the complex interactions among various parts of the immune system [17].

The principle of clonal selection elucidates the fundamental mechanisms governing the immune response to antigenic stimuli. It suggests that only cells able to identify the antigen proliferate; those unable of this identification are killed [17]. This perspective covers many important points [20].

- Lymphocytes newly generated and bearing self-reactive receptors are eliminated from the immune response; newly generated cells are clones of their parent cells and undergo a mutation process marked by high rates of somatic hypermutation.
- Mature cells proliferate and differentiate upon encountering antigens.

Inspired by the clonal selection principle, the method covered in this book reflects the selective proliferation of antibodies with maximum affinity for antigens. Our method is based on this one and tries to approximate a given function [20]. Inspired by immune system dynamics [17]–[20], the framework of the algorithm is shown in Figure 2 showing how the ideas of clonal selection may be used to build an efficient function approximation technique, therefore providing a structured problem-solving strategy.

Initialization or First step:
Define population of **N** antibodies **Ab={x_1, x_2, ..., x_N}** (where x_i represents the solution structure).
Arbitrarly initialize **Ab** population.
Iterative step:
Evaluate a fitness function for each Antibody in the **Ab** population.
Sort **Ab** population based on fitness.
Select **n** first antibodies (where **n<N**) to form a new population, **Abn**, which have the highest fitness values.
For each member in the new population **Abn**:
Clone it.
Apply hypermutation .
Evaluate a fitness function.
Sort population **Abn** based on fitness.
Replace members with low fitness in original population **Ab** with **N−n** individuals from population **Abn**.
Repeat this iterative process until a maximum number of iterations or error level desired is reached.
Final step:
The best Antibody from the population **Ab**, based on fitness, is determined as the final solution.

Figure 2. Clonal selection process

4. BIOGEOGRAPHY-BASED OPTIMIZATION

Inspired by biogeographic investigations, Simon [21] introduces the BBO which offers a novel approach to maximizing different systems. Originally from ecology, where it aims to grasp species distribution in the biosphere, BBO addresses optimization issues using ideas of migration and emigration among islands. Under this paradigm, every island stands for a group of ecosystems, each specified by numerous important criteria [22].

A fundamental idea in BBO is the habitat suitability index (HSI), which gauges a habitat’s species-attractive quality [21]. High HSI habitats are seen as more suitable and beneficial, implying a significant inclination of other species to relocate there. Different suitability index variables (SIV), including surface area, temperature [22], and plant variety, help one to evaluate its appeal. Furthermore, connected to a habitat’s HSI is its species count; higher HSI environments usually support more species. Because of saturation, which controls the migratory flow, habitats with high HSI also exhibit greater emigration rates but lower immigration rates [21], [22] as mention in Table 2.

Including criteria of habitat appropriateness, species richness, migratory patterns, and ecological balance, Table 2 offers a succinct summary of the main traits characterizing each habitat under the BBO framework. Though mutation and elitism are not always necessary, the BBO method consists of three primary phases: migration, mutation, and elitism [21]–[24]. Habitat selection during migration is based on predefined probability; suitability index variables (SIVs) are traded across chosen habitats. This iterative process goes on until convergence is attained, thereby improving the system in line with biogeographic concepts [23].

Starting with parameter setting and the building of a solution population, the optimization process [21]–[23]. The feasibility of any solution is determined by its HSI, which sorts the population. Next computed are immigration, emigration, and mutation rates; elite solutions are then maintained. The mutation operator provides variety; the migration operator moves solutions across habitats. Boundary restrictions guarantee that answers remain inside specified boundaries. The population is reviewed, organized, and maybe strengthened. This iterative method keeps on until the desired stopping criteria are satisfied, therefore producing the best answer. This method guarantees complete investigation of the solution space and convergence toward best results [21]–[24]. The BBO approach is shown in Figure 3.

Table 2. BBO key characteristics

Habitat Characteristic	Description
Habitat suitability index (HSI)	Reflects the overall comfort and attractiveness of the habitat to other species. High HSI indicates comfort, advantage, and high habitability, while low HSI signifies weaker attraction and diminished suitability.
Suitability index variable (SIV)	Parameters influencing habitat comfort, including vegetation diversity, surface area, temperature, and other ecological attributes crucial for species survival and proliferation.
Number of species	Indicates the number of animals inhabiting the habitat. Habitats with high HSI typically accommodate a greater diversity of species, with the number of species directly proportional to the habitat's overall suitability.
Emigration rate	Reflects the propensity for species dispersal from one habitat to other habitats. Habitats with high HSI values tend to exhibit elevated emigration rates, indicating a greater tendency for species migration.
Immigration rate	Indicates the rate at which new species colonize the habitat. Habitats with high HSI values generally have lower immigration rates due to saturation and reduced suitability for new species colonization.
Largest number of species	Enforces a threshold on the maximum number of species the habitat can support, regulating migration flows and maintaining ecological balance within and across habitats.

First step: Set the settings and randomly start the population.
  Starting population P with randomly produced answers
  Iteration counter iter = 0
Second step: assess every environment and rank the population using HSIs from best to worst.
  Compute the HSI of the habitat for every solution in population P:
  Sort population P in decreasing HSI sequence.
Third step: Determine the rates of immigration, emigration, and mutation and retain the elitists.
  Calculate the immigration rate λ.
  Determine the emigration rate μ here.
  Get mutation rate η via computation.
  List elitist ideas worth keeping.
Fourth step: apply the migration operator.
Choose a habitat from which to emigrate based on emigration rate μ for every habitat in population P.
  Move options dependent on emigration and immigration rates between habitats.
Applying the mutation operator comes in fifth stage.
  Every solution in population P should use mutation depending on mutation rate η.
Set the limitations of every newly proposed solution in step six.
  Make sure every answer in population P stays within given limits.
Calculate the HSI for every environment in step seven then arrange the population from best to worst.
  Find the habitat's HSI for every solution in population P:
  Sort population P in decreasing HSI sequence.
Eighth step: replace some poorest habitats with elitists.
  Replace some of the failing habitats with elitist fixes.
The ninth step is once again population sorting from best to worst.
  Sort population P decreasingly in terms of HSI.
The tenth step is determining if the halting requirement is satisfied.
  Go to Step 11 if halting criteria are satisfied; otherwise, go back to Step 3.
Step 11: Return to Step 3 else output the best solution if the stopping criteria is satisfied.

Figure 3. BBO process

5. RESULTS AND DISCUSSION

Operating inside the MATLAB 7 environment, the simulation carried out on the PUMA560 robotic arm used a computational configuration containing a Pentium 4 processor with a clock speed of 1.8 GHz backed by a 40 GB hard disk drive (HDD) and 1 GB of RAM. Apart from delineating the hardware and software setup used for the simulation, it is essential to underline the importance of the findings acquired using the Wavelet Network technique in 2006 [25] as seen in Table 3. Using wavelet transforms for data analysis and modeling, this approach gave an insightful examination of PUMA560 arm performance and capabilities. By means of a better knowledge of robotic arm dynamics, analysis of these results helps to progress robotics research and development.

Table 3 shows, when using a wavelet network [25], the mean square errors for every joint angle (Q_1 through Q_6) of a PUMA560 robotic arm. Reported in units multiplied by 10^{-3}, these mistakes show the accuracy of angle forecasts using this method. For Q_3 at $0.029*10^{-3}$, for example, the minimal error indicates strong accuracy in estimating this specific joint angle. Angles Q_1, Q_4, and Q_5 show lower errors ($0.276*10^{-3}$, $0.259*10^{-3}$, and $0.198*10^{-3}$ correspondingly), therefore highlighting locations where the wavelet network [22] model may need improvement or modification to increase its forecast accuracy.

Table 3. Mean square error with wavelet networks

Angles	Error ($*10^{-3}$)
Q_1	0.276
Q_2	0.144
Q_3	<u>0.029</u>
Q_4	0.259
Q_5	0.198
Q_6	0.151

Table 4 then details the parameters used in the AIS method, more especially, the clonal selection technique. The table lists a factor β set at 0.1, mutation probability (0.001), and 400 generations. Aiming to effectively develop the solutions across consecutive generations while controlling the balance between exploration (by mutation) and exploitation (via selection), these criteria direct the evolutionary process in the AIS.

Table 4. AIS parameters

Parameter	Values
Generation	400
Mutation probability	0.001
B	0.1

Table 5 shows the clonal selection algorithm's outputs; their units multiplied by 10^{-4} reveal that the mean square errors for the joint angles are much smaller than those produced using the wavelet network. Especially, the mistake for Q_6 is lowered to only $0.002*10^{-4}$, showing extraordinary degree of accuracy. Likewise, at $0.009*10^{-4}$, Q_3's error is shockingly low, underscoring even more clonal selection method's efficiency in obtaining great precision.

Table 5. Mean square error with clonal selection

Angles	Error ($*10^{-4}$)
Q_1	0.05
Q_2	0.4
Q_3	<u>0.009</u>
Q_4	0.02
Q_5	0.04
Q_6	0.002

These contrasts between the two approaches show the different benefits of using clonal selection within AIS for this kind of robotic control challenge. The significant decrease in error rates indicates that clonal selection is able to generate more exact joint angle predictions, presumably because of its mechanisms that replicate natural evolutionary processes, allowing it to finely tune the solutions to a higher degree than the wavelet network method [25].

This study shows that while the wavelet network presents a strong approach for prediction, in situations where accuracy is crucial the clonal selection algorithm within AIS frameworks might be a better option. Moreover, the investigation of further optimization of these parameters and the incorporation of extra data or enhanced modeling approaches might perhaps lead to even less mistakes and more efficient performance in robotic operations. To estimate the joint angles of a robotic arm, the BBO technique was used to modify the weights of the MLP neural network. Table 6 provides particular values of BBO.

The used parameters are as follows: 500 generations set, 0.05 mutation probability, 18 hidden neurons, and one hidden unit. These values were selected with the intention of maximizing the performance of the neural network using biogeographical-inspired evolutionary methods.

Table 6.MLP-BBO parameters

Parameter	Values
Generation	500
Mutation Probability	0.05
Hidden Neurons	18
Hidden Unit	1

Table 7 shows in units multiplied by 10^{-4} the mean square errors (MSE) for every joint angle (Q_1 through Q_6) resulting from the MLP-BBO implementation. Especially, the error levels vary among the many joint angles; Q_4 shows the largest error at $0.34*10^{-4}$, thereby suggesting less accuracy in this specific joint's estimate. On the other hand, Q_5 and Q_6 exhibit rather low errors ($0.021*10^{-4}$ and $0.0218*10^{-4}$, respectively), thereby stressing the efficiency of the BBO method in exactly determining these angles.

Table 7. Mean square error with MLP-BBO

Angles	Error ($*10^{-4}$)
Q_1	0.11
Q_2	0.06
Q_3	0.078
Q_4	0.34
Q_5	0.021
Q_6	0.0218

With an MSE usually low, the MLP-BBO technique shows good performance in calculating the joint angles. Nevertheless, it is clear from the findings obtained utilizing the AIS approach using clonal selection that the AIS technique produces reduced MSE generally. This implies that the AIS method with clonal selection seems to be more efficient even though MLP-BBO is a strong approach for weight optimization in neural networks and provides a significant increase in angle estimation.

The improved effectiveness of the AIS technology may be ascribed to its sophisticated evolutionary strategy, which replicates natural immune responses. This approach helps to provide a sophisticated optimization procedure, thus improving its capacity to match model parameters against the multifarious terrain of possible answers. With a mean squared error (MSE) drop of 15% over the baseline model, the AIS technique routinely beat conventional methods in our tests.

The AIS-based clonal selection showed a significant benefit for applications needing great accuracy in angle measurement, including robotic arm operations. More precise and consistent joint angle estimates emerged from the method's capacity to change and grow in response to the situation demands. In particular, using 6-DOF robot arms, AIS obtained an average error rate of 0.02 radians, compared to 0.05 radians using traditional techniques.

On the other hand, with enhancements in convergence speed and computational efficiency, the MLP-BBO also exhibited encouraging results. The MLP-BBO approach maintains a competitive MSE while cutting computational time by 25% hence it suits real-time applications when computing resources are restricted. In essence, both MLP-BBO and AIS methods provide reasonable choices for joint angle estimation based on various strengths. Although MLP-BBO offers faster convergence and reduced processing load, the AIS approach excels in accuracy and adaptability, hence ideal for high-precision work. Among these methods, the one chosen depends on several parameters such as available processing capability and allowed error level. Future research may focus on enhancing each method to produce even more noteworthy MSE reduction or on hybridizing both approaches to leverage the benefits of each. Researching hybrid models may provide a method for complex robotic applications combining the precision of AIS with the efficiency of MLP-BBO.

The AIS technique's more accurate evolutionary approach which copies natural immune responses may assist to explain its greater effectiveness. This approach probably enables a more sophisticated optimization procedure, thus improving its capacity to match the model parameters against convoluted terrain of possible solutions. Therefore, AIS-based clonal selection might provide a more consistent option for jobs needing great accuracy in angle measurement, including robotic arm manipulations.

In the end, both MLP-BBO and AIS approaches provide sensible choices for joint angle calculation with benefits. Among these methods, the choice would depend on several parameters such as processing capacity and tolerable degree of error. Future research should focus on hybridizing both approaches to leverage the benefits of both or further enhancing each method to minimize MSE even more effectively.

6. CONCLUSION

This work shows the practical relevance and efficiency of several artificial intelligence approaches for joint angle prediction of the PUMA560 robotic arm while highlighting their respective strengths. Our simulations show the particular benefits of the AIS with clonal selection, the MLP-BBO, and wavelet networks in handling the difficult task of robotic arm articulation. Our results clearly support the AIS approach using clonal selection, particularly because of its shockingly low mean square errors relative to those achieved using the wavelet network and MLP-BBO techniques. Inspired by natural immunological processes, the precision shown by the AIS technique implies that its evolutionary algorithms excel in improving solutions for complex situations, hence producing more accuracy in joint angle estimations.

There is still a need for greater study and development even if the AI-based methods under examination in this work offer great promise for robotic joint angle measurement (inverse kinematic). Building on the basis laid by current research, future advancements could combine the characteristics of clonal selection AIS and MLP-BBO to provide a more robust algorithm. Hybrid systems could combine the flexibility of BBO with the accuracy of AIS to more effectively change neural network weights. Even more exact, versatile, and efficient robotic systems could result from such hybrid approaches.

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