Innovative Solutions for IK: PROA and Clonal Selection Algorithms Unveiled

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Abstract: - Calculating joint angles for sequential manipulators consists of studying the correlation between Cartesian and joint variables. The problem-solving technique encounters two main hurdles described as direct and inverse kinematics. Matrix multiplications usually simplify the direct kinematic problem. However, inverse kinematic problems are harder as they require solving many nonlinear equations and eliminating variables a lot. In our work, we introduce two new methods of handling the complicated inverse kinematic problem for robotic manipulator arms; Poor and Rich Optimization Algorithm and Clonal Selection Algorithm (CSA). These advanced techniques enhance greatly the estimation of various joints in the arm which makes the solution more precise and efficient. To demonstrate the effectiveness, robustness, and potential benefits of these approaches for complicated kinematic problems we present extensive simulation results thereby enabling better performance of robots.

Key-Words: - Articular angles, Poor and Rich Optimization Algorithm, CSA, manipulator, direct kinematic, inverse kinematic.

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1 Introduction

Robotic arm kinematics can estimate the angles and positions of a robot arm’s joints for reaching a specific end-effector position. Inverse kinematics commonly solves this, [1].

Within different industries inverse kinematic process has its’ own specifications and challenges, [2]. In manufacturing automation robot arms are used for tasks such as welding, packaging, assembling, or painting.

Their exact articulation ensures precise results and efficient pick-and-place operations. In medical rehabilitation, robots are used to assist patients in physical therapy by tracking movements with great accuracy; whereas during delicate surgeries where safety matters most of all, such machines should be able to estimate each move they make. Among other service robots that working great when being articulated accurately there can be mentioned those designed for disabled persons'care or housekeeping needs (for example – vacuum cleaners), [3]. For instance, the ability to estimate articulation accurately can be used in robotic learning or HRI research and development since it enhances robots ‘ adaptability and safety during interaction with humans, [3].

Autonomous robots in agriculture are expected to manipulate things and explore territories correctly while maintaining plants that harvest and monitor crops. In warehousing and logistics robots assist in sorting packages automatically picking them from storage places and locating them in designated areas hence the need for accurate movement estimation during their operations to enhance productivity, [4]. The entertainment industry as well as media houses use robotic arms for creating animated characters that seem humanlike and stage crafts that are attractive to clients. Finally, in space science, these machines serve purposes such as maintaining repairing carrying experiments out on space craft or even rovers stationed at different planets within our solar system thus should be articulated with precision to function well under extreme conditions, [5].

Depending on the complexity of the robotic system and the specific application, inverse kinematics (IK) may be difficult. Inverse kinematics is challenging due to a variety of factors, [6], [7], [8], [9]. Solving nonlinear equations which can be complex and require a lot of computational power is common in mathematics for IK problems. Additionally, singularities may cause the robot to lose degrees of freedom hence making some equations unsolvable or infinitely solvable and there are multiple potential solutions for various configurations of robots which makes it hard to select the best one. Robot configuration also matters; IK becomes complicated in systems with numerous kinematic chains or several degrees of freedom (DOF) like humanoid robots, [8], [9].

For instance, IK problems concerning real-time operations like robotic surgery and interactive robots are challenging because they require quick and accurate computation solutions. Moreover, such problems become more complex when physical limitations, for example, joint restrictions or collision avoidance come into play. Numerical methods offer flexible ways of dealing with these issues which include the use of the Jacobian inverse but they may fail due to high computational costliness caused by their flexibility or lack thereof as well as non-convergence issues related to gradient descent while analytical methods provide exact answers but are often limited to simpler configurations, [8], [9].

Despite these challenges, advances in methods and tools (e.g. machine learning strategies, optimization techniques, or Jacobian inverse), have significantly improved the controllability of IK for a diversity of robotic applications. While IK has challenges in computational, mathematical, and physical sense there have been a lot of improvements over time that have improved its applicability and performance for different applications, [8], [9].

The Table 1 enumerates developments in the use of neural networks and evolutionary algorithms for inverse kinematics solving as of late. [10], proposed a hybrid strategy that fuses genetic algorithms (GA) and neural networks. This is illustrated in the following table highlights new works based on neural networks and evolutionary algorithms applied to the IK problem. [10], suggested the use of GA along with neural networks but the approach was a mixed strategy. This method minimizes the likelihood of end-effector faults with very small accuracy by creating an initial population for the GA by three off-Elman neural networks. The studies were performed on a six-axis serial robot platform.

Another method named semantic niching technique that is adaptive in its nature was proposed in [11] and has employed a local search-based quasi-Newton algorithm in combination with niching genetic algorithm. It added significantly to the findings of the simulation, whatever the particular system under examination had not been stated yet. The self-adaptive mutation rate in the genetic algorithm was proposed in [12], along with combining sequential mutation genetic algorithm with extreme learning machine. The ELM was used first to calculate the first IK solution and then GA with its basic steps WHERE used for further optimization. Stanford MT-ARM robotic manipulator with six degrees of freedom (DOFs) was used to implement and test this approach with improved performance in terms of increased speed of processing and the ability to give as many and as accurate Inverse Kinematics solutions as needed.

Table 1. Overview of Research on IK Solutions for Robotic Manipulators

Author	Approach	Key Techniques	System Tested	Results
[10]	A hybridapproach using neural networks and GA	Three Elman neural networks for the initial population	Six-axis serial robot	Achieved high precision in end-effector error minimization
[11]	Adaptive niching strategy	Niching genetic algorithm, quasi-Newton algorithm	three KCs of a modular robot	Improved precision and resolution of simulation results
[12]	Sequential mutation genetic algorithm combined with extreme-learning machine	Extreme-learning machine for preliminary IK solution, simple GA for optimization	Stanford MT-ARM robotic manipulator (6 DOFs)	Improved computational time without reducing the accuracy of IK solutions
[13]	Continuous genetic algorithm	Continuous GA operators for initialization, crossover, mutation	3R planar manipulator	Smoothened joint space while maintaining the accurate Cartesian path

[13], employed a continuous genetic algorithm and used the CGA operators for initializing, selection, crossover, and mutation. In their experiment, they applied their method on a 3R planar manipulator and proved that their approach was advantageous at the Least Squared cost function since it smoothed the joint space and kept the Cartesian route accurate without losing the Cartesian path whereas proved continuous GA as effective to generate exact IK solutions.

The so-called inverse kinematics (IK) problem has to be solved in the field of robotics in order to enable the precise and adaptable motion of robotic arms and manipulators. IK issues present considerable challenges because they often involve complex and non-linear relationships, and there are multiple solution possibilities with varying optimalities. Such problems characteristically possess vast solution spaces that are irregular and complex for classical techniques to manage. On the other hand, new approaches for solving these problems appeared with the main group of newly emerged optimization algorithms as the “Poor and Rich Optimization Algorithm” PROA) [14], [15], [16], [17] and the “Clonal Selection Algorithm” (CSA) [18], [19], [20], [21], [22], [23].

Because of its two-methodology method [14], the application of the PROA on the IK is also particularly appealing because it resembles the dynamic requirements of IK solutions for robotics. Taking the use of the social terms “rich” and “poor” groups, PROA provides a clear divide between more harm-oriented means of optimization [14], [15], [16], [17], and more beneficially-oriented ones. The population is basically split into two subpopulations by this algorithm: In terms of local exploitation, it is referred to as the “rich,” which exploits the potential places utilizing the local search, and the “poor,” which tries to search an area within the entire solution space by using the global search. Like the discussed tiered approach that uses different forms of the memory system to ensure there is progressive learning or development while also ensuring that there is a fast search through the complex solution spaces that are characteristic of most robotic joint configurations. This functionality is rather beneficial for real-time iterative apps where the speed of convergence and performance increment of even a few percent means a lot, [14], [15],[16], [17].

Likewise, the CSA [18], [19], [20], [21], [22], [23] offers a robust background for tackling the IK challenge because it relies on immunological clonal choice principles. This method works as a form of an ‘antibody’ that is aimed at the afflicted ‘antigen’ of the target end effector site through mimicking the Biológical evolution processes of the B cells that affords affinity maturation and selection. Finally, as with CSA, it starts with a wide range of initial solutions and focuses on locating and making copies of high-performing solutions and using hypermutation, [19]. This selection and mutation course is most acceptable and aligned to the complicated situation of IK where there are several joint configurations that could achieve the intended goal with different levels of effectiveness, [18], [19], [20], [21], [22], [23]. CSA is actually very successful when robotic systems are required to remix from one pre-established task to another as CSA has the ability to learn and develop new approaches, [22].

With improved applicability offered by using PROA and CSA, scientists and engineers may be able to use effective techniques towards enriching the versatility and feasibility of robots in solving problems that require kinematic inverse solutions. These are cutting-edge approaches to robotic interface that create way to advanced robotic systems that are even more sensitive and adaptive to the environment and at the same time create new frontiers of robotic automation.

The rest of the paper is arranged as follows: The rest of the paper is arranged as follows:

• Part 2: Robotic Arm, this section then goes deeper into describing the PUMA 560 robotic arm manipulator in detail its features and size, and lastly stresses the need to find a proper solution to the IK problem to enable accurate and adaptive control of it.

• Part 3: Poor Optimization Algorithm (PROA), let us discuss about that technique and implementation of the Poor Optimization Algorithm. In this section, the primary emphasis is made on the fact that PROA has specific benefits and unique characteristics, which deal with the enhancement of the quality of the IK solution through the application of the developed approach based on the use of complex arrays of stimuli.

• Part 4: that part considers more in detail the Clonal Selection Algorithm, exploring the ideas and solutions behind it. This paper explores the application of methodologies borrowed from the field of immunology to solve the IK problem in the case of CSA with the objective of establishing the applicability and effectiveness of the concept.

• Part 5: PROA and CSA simulation experiment on the PUMA 560 robotic arm. In this part, the simulation outcomes acquired using the PROA and CSA models are described. We compare the accuracy of both algorithms and then give an analysis of the findings which have further implications for the field of robotics.

• Part 6: Recommendation, the last segment of a report provides a summary of critical observations that may have been derived from the inquiry. Finally, it accredits the contributions of the study to the advanced optimization techniques in robotics and suggests direction for further research in enhancing the prospect and applicability of these methodologies.

2 PUMA 560 Arm

Robotics is an organized method of command and execution to enforce the desired task by combining mechanical, electrical, and computational technology. It begins with the initial stage of sensation of the environment followed by an analysis of the sensations by specific algorithms to produce a set of instructions for the movement of the motor.

These are instructions issued to guide and instruct mechanical parts into accomplishing work that has been anticipated, and as such you look at the mechanical components to ensure that they heed the instructions given to them.

However, the scope of the system is within the reach of the robot's manipulator, which is usually mounted on a rigid element, for example, the floor or ceiling, and consists of several links and joints; the working area is sometimes called the workspace. The end-effector denotes the tool mounted on the terminal link of the manipulator, which performs the specific task. End-effectors are tools and products such as scalpels, graspers, and needles that are used during surgery.

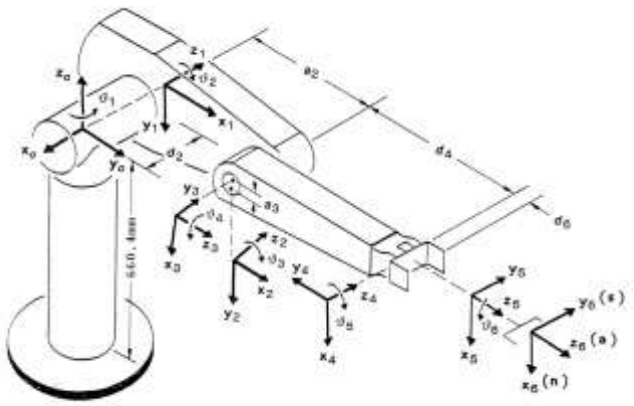

Fig. 1: PUMA 560 arm

In a PUMA560 type robot, six rotational joints are represented by variable Q1 to Q6 as depicted in Figure 1, and in order to make the system work, one has to find these angles q1, q2...q6 for the robotic arm ("end-effector") relative to the End-Effector point M(x,y,z) in a Cartesian plane and they can be inserted into the manipulator equation, thus the equations obtained are finished. After the joint angles were determined, they made the output of the joint parameters Q which are represented by the vector Q (Q1, Q2, Q3,..., Q6).

The process of finding the joint parameters, which are represented by the vector Q (Q1, Q2, Q3,..., Q6) is as follows:

Enter the coordinate of the M point in Cartesian space

Apply an optimization method ***f*** that minimizes ***norm(f(Q) – M) = 0***.

3 Poor and Rich Optimization Algorithm

The Poor and Rich Optimization Algorithm (PROA) which is a multi-population optimization technique based on socioeconomic concepts relies on [14], [15], [16], [17] references. It has implementation of a stratification-based algorithm that divides the population into rich and poor classes. The rich group includes subjects with higher fitness values and the poor one comprises those with lower fitness values. PROA modifies solutions iteratively using different tactics for each group. For affluent subpopulations, intensification prevails as its guiding principle, the algorithm gives preference to exploitation by carrying out small changes in solutions to gain better ones locally, [15]. Conversely, the underprivileged subpopulation approach focuses on diversity; making big changes/manipulations to explore new regions in the search space, [15].

PROA picks a method that uses the average of the top, middle, and bottom picks from the rich group, [16]. This approach guides the less rich group toward better choices. By mixing these ways, PROA keeps a good balance between trying new things and sticking with what works, [16]. It also adds steps for changing, combining, and ordering groups to keep variety and make sure of ending up with the best answers. PROA's way of doing things from many angles helps it solve tough problems well, [16], [17].

Fig. 2: PROA flowchart

This is just a simple explanation [14], [15], [16], [17] of PROA in the form displayed by Figure 2, [17]:

- Start by employing random candidates to form a deprived early population.
- By combining those found through searching the neighborhoods and those found randomly you create a starting 'middle class'.
- Assess each candidate solution in terms of its appropriateness for both rich and poor communities.
- Let the number of candidates to be moved from rich to poor be determined by a method that is based on probability.
- According to the number of iterations that were completed, re-distribute the ratio of rich and poor people at different points in time.
- Diversify the search process by modifying random solutions in both groups.
- Continue steps 3 to 8 until a stop criterion is met (e.g., maximum number of iterations or finding a feasible solution).

4 Clonal Selection Algorithm

Artificial Immune Systems (AIS) fall in the category of computer simulations of the immune system which help immunologists do difficult/impractical research that is not possible to solve using other approaches, predict the future, and run simulations and trial runs. Another name for this topic is computational immunology, [18], [19], [20], [21], [22], [23]

This branch is growing very fast at present and its goal is to develop computer models that simulate the mechanisms of mammalian immunity. These systems are focused on the ability of a body to recognize foreign substances, and antigens, and destroy cancer cells without damaging normal human cells, [18], [19], [20], [21], [22], [23].

Immune Network, Clonal Selection, and Negative Selection are among the important algorithms in this area, [18].

The comprehension of immunological responses to antigens is based on the principle of clonal selection. It conveys the idea that immune cells will proliferate and be selected (recruited) only if they can recognize and bind to antigens, instead of immune cells that do not associate with antigens, [18].

Based on the above, it can be summarized thus:

- cloning immune cells which are likely to mutate with a possibility of mutations, or somatic hypermutation, [18], [19], [20], [21], [22], [23].
- The elimination of newly generated lymphocytes with self-reactive receptors and, development and maturation of naive cells that respond to antigens.

Our algorithm extends the Clonal Selection paradigm when it is made clear that only antibodies with the highest affinity for antigens are picked to proliferate. In effect, our approach combines the principles of clonal selection and function approximation. Below is the algorithm [23], together with the flowchart shown in Figure 3:

1. The initial settings

Establish Base Population: Generate random population within given limits.

2. Main Loop: Perform operations until reaching the point where the stop is required.
   - Calculate Affinity: Get the affinity of each individual in the population.
   - Choose Top Individuals: Select the best individuals depending on affinity.
   - Create People for Cloning Based on Clone Rate: Some people were selected for cloning using the clone rate criterion.
   - New Affinities From Hypermutation Of Clones Are Produced: The clones have new affinities through hypermutation.
   - Updatting population: this is made by selecting the best individuals from (Original And Cloned Populations) to keep up with population change
   - Introduce Randomness (to Ensure Genetic Diversity): Form and pick out random new people to maintain genetic diversity.
   - Go to the next iteration by incrementing the loop counter.

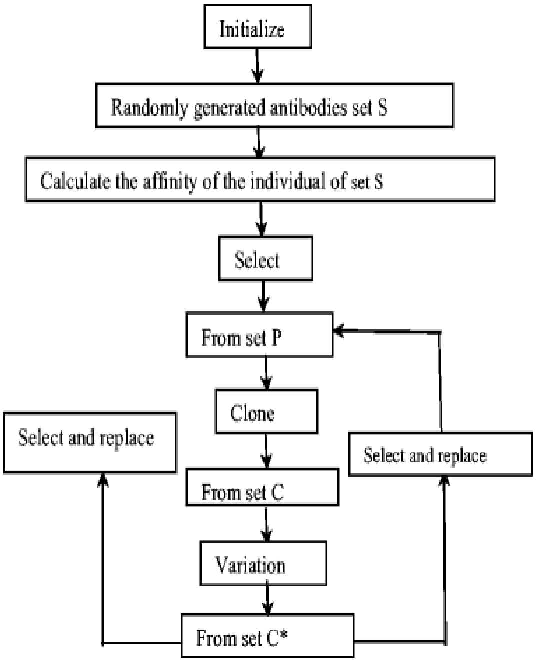

Fig. 3: Clonal selection flowchart

5 Experimentation and Results

A Pentium 4 with 1.8 GHz CPU was used to simulate the PUMA560 robotic arm on the machine. The system configuration consists of one 40 GB hard drive and 1 GB RAM, with Matlab 7 as the simulation environment.

The Poor and Rich Optimization Algorithm (PROA) and the Clonal Selection Algorithm (CSA), as well as the application of these methods, have resulted in great improvement in the performance and flexibility of robotic arms and manipulators to cope with the difficulties of inverse kinematics (IK). Here, we will show the results of applying the two optimization methods to tackle the nonlinear and complex characteristics of IK issues and a comparison with the Wavelet Network method's 2006 findings, [24].

To improve the performance and reflexivity of robotic arms and manipulators the poor and rich optimization algorithm (PROA) and the clonal selection algorithm (CSA) are the biggest breakthroughs that have been seen in the aforesaid problems of IK difficulties. This section is dedicated to demonstrating the application of these two novel methods of optimization in solving the nonlinear and intricate nature of IK problems as well as to discuss the insights from our own implementation experiences and the comparison as well as the Wavelet Network method's 2006 findings, [24].

The Table 2 gives the values of the mean square error (MSE) by the wavelet network method at the six different configurations (Q1 to Q6). The errors scaled down by a factor of 10^{-3}, signify that Q3 (0.029) is the position with the least error, and that Q1 (0.276) is the one with the biggest error.

Table 2. MSE with Wavelet Networks

Angles	Error ($*10^{-3}$)
Q1	0.276
Q2	0.144
Q3	0.029
Q4	0.259
Q5	0.198
Q6	0.151

This variability in error reflects the effectiveness and accuracy level of the Wavelet Network method in solving inverse kinematics problems for different configurations.

The Artificial Immune System (AIS) algorithm's parameters are listed in the Table 2. The number of generations was set to 400, with a mutation probability of 0.001, and the parameter β was set to 0.1. These characteristics were crucial in determining the AIS's behavior and performance during the optimization phase as shown in Table 3.

Another tuned parameter is the Mutation probability, which was set to 0.001, with a mutation rate of 5% for each gene and the β was set to 0.3. These characteristics were the ones that significantly influenced the behavior and the performance of the random elements of the AIS at the optimization phase.

Table 3. CSA parameters

parameter	Values
Generation Number	400
Mutation Probability	0.001
β	0.1 and 0.3

Table 4 is a detailed, vivid, and informative table presenting the Mean Square Error (MSE) values of six different robotic joint angles (the first through the sixth) after the Clonal Selection Algorithm (CSA) has been applied to them. The values are presented as coefficients of 10^{-3} and thus indicate great deviation between the performance of the different links or variances across joint angles. One way to interpret it is: that a figure of 0.002 indicates a negligible error, therefore, the corresponding joint Q6 assembly is practically error-free. On the flip side, the highest error produced at joint Q2 was 0.4, which is enough to show that the method might benefit from more development.

Table 4. MSE with CSA

Angles	Error ($*10^{-3}$)
Q1	0.05
Q2	0.4
Q3	0.009
Q4	0.02
Q5	0.04
Q6	0.002

As a whole, these researches show that the CSA is a powerful and flexible approach in dealing with the inverse kinematics problems, which are the most challenging part of the activity on the robotic system.

The data not only verifies the CSA technique's reliability but also brings to the fore some of the details underpinning its operational subtleties and the possibilities for optimization in real-world robotic applications.

Table 5. MSE With PROA

Angles	Error ($*10^{-3}$)
Q1	0.03
Q2	0.054
Q3	0.00015
Q4	0.014
Q5	0.098
Q6	0.003

A summary is given in the Table 5 of the Mean Square Error (MSE) values obtained using the New and Better Optimization Algorithm (NOA) for the six different robotic joint angles (Q1 to Q6). These figures, which are scaled ata factor of 10^{-3}, show algorithm's ability to attain accurate performance in the different establishments. In the most error-free case, Q3 is displaying a tiny 0.00015, thus underlining the flawless performance of the algorithm in a certain environment. On the other hand, Q5 exhibits the biggest error of 0.098 which indicates that the robot can be improved its performance by some tuning of the algorithm. From our side, the upcoming part explores the robustness of the PROA method. It also discusses the possible pitfalls of this method if it is not correctly used for accurate control and adaptation in difficult robotic kinematic situations.

A comprehensive comparison of three optimization strategies: PROA, CSA, and Wavelet Networks employed in robotic arm joint rotations (Q1 to Q6) provides an uneven playing field of algorithmic effectiveness.

Let me give you an analysis here:

- Q1: The lowest error ($0.03*10^{-3}$) of PROA exhibits justification of PROA as best among the rest and thus more accurate. This earned PROA first place among the accuracy requirements that are as difficult as the first example.
- Q2: PROA made a significant success in Q2 with a huge descent in MSE ($0.054*10^{-3}$) while CSA had a bigger error ($0.4*10^{-3}$). As such, PROA proves to be a useful tool for faster optimization under Q2 conditions.
- Q3: PROA is more effective in comparison to both CSA and Wavelet Networks with an almost zero margin of error ($0.00015*10^{-3}$), thereby expressing excellent accuracy and sensitivity in the precision calibration settings on the robot.
- Q4: PROA has the MSE reduction factor which is the greatest, illustrating the strong capacity of the PROA even with the most intricate and convoluted situations, and as a result, the greatest error reduction to $0.014*10^{-3}$ in all joint configurations.
- Q5: The two algorithms have the same error rates $-0.04*10^{-3}$ and PROA ($0.098*10^{-3}$) had errors, too. These algorithms have lower errors than the Wavelet Networks, whereas CSA has the lowest MSE, showing that it is more promising in joint Q5.
- Q6: Both CSA ($0.002\ *10^{-3}$) and PROA ($0.003*10^{-3}$) exhibit minimum mistakes and high efficiency isthe most efficient, with CSA in particular coming out ahead of PROA in this case.

What can be gathered, PROA consistently betters the rivalries in the main but on the other hand, it is extremely low in MSE and the best in precision and optimization. This is particularly evident in scenarios that need high levels of accuracy, such as Q1, Q2, Q3, and Q4. CSA is also an excellent support of the specific arrangements namely Q5 and Q6, where it is slightly ahead of PROA, to indicate its potential for some distinct purposes. This research proves the significance of picking the algorithms according to the operational requirements of the robotic system to have exceptional performance and be adaptable.

6 Conclusion

PROA, CSA, and Wavelet Networks, are the three optimization algorithms used in this study. For solving the inverse kinematics of the robot arm, we are using a PUMA 560 robotic arm manipulator. This study was primarily concerned with decreasing the Mean Square Error over the whole joint (Q1–

Q6) set upto identify the method that offers precision and the least use of energy.

In most cases, it is notable that the use of the Poor and Rich Optimization Algorithm (PROA) is more favorable to the other methods, synchronically in Q1, Q2, Q3, and Q4. This is the true test according to the competitiveness of PROA in the set of movements that are complex and fluctuating, the realization of PROA as the stand-out choice for the applications requiring high precision and excellent performance is clear.

The Clonal Selection Algorithm (CSA), though it has some restrictions in Q2, is very effective in Q5 and Q6. Its outstanding performance in the creation of these specific joints shows its ability to shape a variable tool that would adapt and respond dynamically and thus can be used purposefully wherever flexibility and specificity are paramount.

Fortunately, Wavelet Networks, among other algorithms that have become obsolete, still provide some foundational reasoning when studying the evolution and development of the algorithmic strategy over the years. The obvious performance lag hints at the remarkable developments in the domain of robotics inverse kinematics.

Therefore, the main stress of the article lies in the role of the algorithm in the robotic system design and implementation.

This study's results are a piece of helping for knowing the best driving digital systems for specific tasks, but they also contribute to robotics part by increasing our understanding of the fact that different optimization techniques can be used to improve the adaptability and efficiency of the robotic systems.

Progress made in the robotics field will often be directed by the conclusions of this research since we will be able to execute efforts to figure out why some of the robots are capable of adapting to changes faster and more accurately than others.

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Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the author used Quilbot Grammar Checker in order to improve readability and grammar. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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Conflict of Interest

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