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Comparative Analysis for Machine-Learning-Based Optimal Control of Upper Extremity Rehabilitation Robots †

Muhammad Kamran [1], Talha Ahmed Khan [2,3,*], Umar Iftikhar [4], Safdar A. Rizvi [2], Irfan Tanoli [5] and Kushsairy Kadir [6]

1 Harbin Institute of Technology, Harbin 150001, China; joyo@hit.edu.cn
2 School of Engineering and Applied Sciences (SEAS), Bahria University Karachi Campus, Karachi 75850, Pakistan; sadiacap@hotmail.com
3 Faculty of Computing, Multimedia University, Cyberjaya 63100, Malaysia
4 Department of Computer and Information Systems Engineering, NED University of Engineering and Technology, Karachi 75250, Pakistan; umariftikhar@neduet.edu.pk
5 Department of Computer Science, SZABIST Karachi Campus, Karachi 75600, Pakistan; dr.irfankhan@szabist.edu.pk
6 British Malaysian Institute, Universiti Kala Lumpur, Kuala Lumpur 50250, Malaysia; kushairy@unikl.edu.my
* Correspondence: ahmedkhan.talha01@mmu.edu.my
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Abstract: It has been observed from many pieces of research and through applications that robotic movements using human interaction are considered dangerous, tiresome and require extraordinary precision and smooth control. Specifically, medical and healthcare applications have been the highest priority in recent years. The concept of rehabilitation using robotics was introduced during the 1980s with the motive of freeing therapists from repetitive work while treating an increasing elderly population requiring physiotherapy. Furthermore, the consistency of the robot's operation and the volume of repetitions has increased. They can assist therapists in performing tedious tasks and let them concentrate on several patients simultaneously. Several types of rehabilitation robot devices have been produced in recent years with different modes of training and control strategies using various control algorithms. In this research paper, a comprehensive overview of rehabilitation in relation to robotics is presented. The main aim is to determine robust controlling optimization for the smooth control of robotic movement, as these movements require a lot of precision and accuracy. The analysis showed that M-PSO was found to be very effective and robust in finding the best optimal values, as the Modified PSO achieved the minimum root mean square value and a best fit of 98.7.

Keywords: upper extremity; rehabilitation; optimization; smooth control

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1. Traditional Controlling Approaches

In rehabilitation robotics, position control is the primary objective when performing an exercise. Mostly PID, PD or PI controllers are utilized to regulate the position of a rehabilitation robot, such as is in the case of ARM-Guide [1]. Motion ARM, based on MIT Manus, was developed, which is also a stationary end-effector-based system with 3-DOF in which two are active and one is passive. It uses brushless DC motors to actuate the motion. The system is utilized to perform shoulder and elbow exercises. Gravity compensation, along with an impedance controller, were used as the controllers for the motors. NeReBot [2] is also a stationary end-effector-based system, which is a 3-DOF corded system for physical therapy. Another researcher in 2008 developed a 3-DOF rehabilitation system [3]. Proportion Integral (PI) and Proportional Derivative (PD) control algorithms have been utilized as controllers, using position and force as input parameters while an impedance control strategy was used. MIME-RiceWrist [4] is a 9-DOF exoskeleton system used to perform shoulder, elbow, forearm and wrist exercises. Maxon electric motors and a capstan drive transmission system are used to actuate the system. Furthermore, impedance control is used in the system, while an inverse kinematics-based task–space position controller is utilized with a proportional derivative (PD) trajectory controller. Another end-effector-based 2-DOF stationary system was developed for rehabilitation. With the assistance of two DC motors, planner motion for shoulder and elbow joints was achieved. A force impedance controller was used to regulate the system. Force and position can be acknowledged as two significant control parameters. ArmeoPower from Hocoma [5] is a 7-DOF with one passive DOF system and six active, and it is able to perform elbow, shoulder, forearm, and wrist exercises. The stationary exoskeleton system uses six DC motor actuators to achieve the desired motion. The rehabilitation system utilizes an impedance controller with gravity and friction compensation. A calculated torque PD controller is used for the system that uses gravity compensation. MUNDUS [6,7] is a wheelchair-mounted exoskeleton system. A sequential-based feedback controller was used for the simultaneous feedback control of the 3 DOFs incorporated within a biomimetic feed forward controller. Just using sequential control can reduce computation time and guarantee very robust accuracy in reaching the target. Gentle/G [8–11] is a 9-DOF rehabilitation system that is stationary, which can allow the shoulder, elbow, forearm, wrist, thumb and other fingers to move together to perform a grasping motion.

2. Intelligent Advanced Controllers

Advanced intelligent controls are mostly used for on-demand support or adaptive control approaches. These types of controllers are based on fuzzy logic, decision-making algorithms, artificial neural networks, and traditional machine-learning-based algorithms to complete rehabilitation tasks. To perform forearm physical therapy, a stationary 1-DOF rehabilitation system was designed [12–15]. Joint angle and torque were taken as input parameters, and active and passive mode training were also provided by the robot. To enable the smooth execution of both modes of training, a fuzzy controller was utilized as a torque controller. A robot manipulator based on 2-DOF was developed with the integration of fuzzy neuro control. For the estimation of how much torque is needed, an EMG surface was used for elbow movement [16–18].

3. Optimization for Controlling Parameter

In recent years, bio-inspired algorithms have received huge attention and are being successfully utilized in many industrial applications. Such algorithms include evolutionary approaches, which are the genetic algorithm, cultural algorithm, differential evolution, Japanese tree frog calling, dolphin echolocation, the flower pollination algorithm, and the great salmon run. In this study, a number of optimization techniques will be analyzed to identify the optimized parameters of a PID controller with a dynamic model of the upper limb rehabilitation system. To determine the optimal control parameters for PID, there exists a number of tuning methods, such as Zeigler Nichols and fuzzy logic, which are classical methods. In contrast with other optimization algorithms for tuning, most of the swarm intelligence-based algorithms achieve increased accuracy and have good reputations in the research community as they have outstanding performance while solving many real-life engineering optimization problems [19,20]. Gaing reported a unique design approach for the identification of optimal PID controller parameters for an AVR system based on particle swarm optimization (PSO). In that research, the performance of the system improved and was more efficient as compared with the genetic algorithm (GA) [21,22]. Table 1 demonstrated comparison for optimization using bio-inspired algorithm is swarm-based intelligence algorithms, including particle swarm optimization, ant colony optimization, bat algorithm, artificial bee colony, cat swarm, cuckoo search, etc.

Table 1. Comparative analysis of the latest optimization approaches.

Approaches	Domain	Features	Merits and De-Merits
Zeigler Nichols and fuzzy logic, which are classical methods 2018	Optimization	PID	Classical methods with above-average efficiency
Particle swarm optimization (PSO) 2004	Optimized PID controllers	AVR System, Optimization	PSO performed better than the genetic algorithm
Controller was optimized using Artificial Bee Colony (ABC) 2018	Controller Parameters were optimized using Artificial Bee Colony (ABC)	Extension of the optimization	Artificial Bee Colony (ABC) produced better results than the PSO in AVR-based systems
Ayas used PSO optimization. 2014	PID controller parameters Optimization	2 DOF rehabilitation robot	Integral squared error was calculated that proved better efficiency of PSO
Mehdi used a 3-DOF planar robotic manipulator system. 2011	Utilized PSO for offline tuning of the impedance controller.	Tuning of impedance controller	PSO performed outstanding compared to existing approaches
Aminizar developed a 2 DOF robotic system for rehabilitation. 2013	The neural network was used in this study as a controller optimization	Genetic algorithm was used for optimization	Neural network generated better results compared to the genetic algorithm
Mandava used Invasive weed optimization (IWO) for tuning PID for a biped robot. 2018	Weed Optimization (IWO)-tuned PID controller is compared in terms of error and the torque required at various joints.	Further IWO-tuned PID controller was tested with 18-DOF biped robot.	Weed Optimization (IWO)-tuned PID controller is compared in terms of error and the torque required at various joints.
Ali worked on 2 DOF upper limb robotic arm, which used fuzzy inference system for online tuning of parameters of PID. 2018	PID parameters tuning	Fuzzy inference system for online tuning of parameters of PID	The system was simulated and had positive results.
Khoury developed a 5-DOF system and applied fuzzy PID control for trajectory tracking problem. 2004	A systematic study was presented for optimizing the tuning parameters of the controller.	Fuzzy PID Control	The performance of the proposed controller was validated with a comparative evaluation of torque and direct adaptive control methods.
Ayas worked on a 2 DOF ankle rehabilitation robot and used a cuckoo search algorithm. to determine the optimal control parameters for fractional-order PID control.	Cuckoo Search algorithm was applied to optimize control parameters for fractional order PID control.	Machine learning-based Cuckoo Search Algorithm	ITAE, ISE and IAE as objective functions were used to evaluate performance criteria.
Mahanta used Artificial Bee Colony to predict inverse. 2019	Inverse kinematic problem.	Kinematic matrix	DOF industrial robot end-effector position is not easy to determine.
H. V. H. Ayala and L. dos Santos Coelho, "Tuning of PID controller based on a multi-objective genetic algorithm applied to a robotic manipulator", Expert Systems with Applications, 2012	PID	2-DOF Robotic Manipulator	Robust, Closed Loop Tracking
H. Ibrahim, F. Hassan, and A. O. Shomer, "Optimal PID control of a brushless DC motor using PSO and BF techniques", 2014	Optimization using PID	PSO	PSO performed outstanding compared to BF.
F. Yan, Y. Wang, W. Xu, and B. Chen, Transactions of the Canadian Society for Mechanical Engineering. 2018	Controlling of Time Delay Parameter	Artificial Bee Colony Algorithm	Cable-driven manipulator control was enhanced by using ABC.
C.-F. Juang and Y.-T. Yeh, IEEE transactions on cybernetics. 2018	Optimization using Recurrent Neural network	Multi-objective Evolution of Biped Robot Gaits	Results achieved with neural network complexity

4. Results and Discussions

Rehabilitation training modes and existing control approaches for rehabilitation robots have been discussed in detail. The control parameter optimization section revealed that most of the controllers have achieved smooth and precise control by applying several machine learning and artificial intelligence-based algorithms. The quantitative analysis for the modified particle swarm optimization was compared to the latest artificial neural network approach, support vector machine, adaptive neural fuzzy system and neural network auto-regressive architecture. The analysis showed that M-PSO was found to be very effective and robust in finding the best optimal values, as the Modified PSO achieved the minimum root mean square value and the best fit of 98.7.

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