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Optimization of Robot Arm Motion in Human Environment

Zulkifli Mohamed[1], Mitsuki Kitani[2], Genci Capi[3]
[123]Dept. of Electrical and Electronic System Engineering, Faculty of Engineering
University of Toyama, Toyama, Japan
[1]Faculty of Mechanical Engineering, Universiti Teknologi MARA, Shah Alam, Malaysia

Abstract: In this paper we propose an optimal arm motion generation satisfying multiple criteria via evolved neural controllers. Three different criteria are chosen to be optimized simultaneously, similar to human arm motion in performing daily activities. These criteria are minimum execution time, minimum distance and minimum acceleration. Selected neural controllers from the Pareto solutions are implemented and their performance is evaluated in simulation and on the real mobile robot. Results show a good performance with some differences between simulation and real robot experiments.

Keywords: Multi-objective genetic algorithm, robot arm motion generation, mobile humanoid robot.

Introduction

In assisting humans in their everyday life activities, humanoid robot arm motion generation is required for moving an object such as bottle, books or a glass of water from one position to another. The arm motion has three basic characteristics which are, time, distance and acceleration. In performing a specific task of picking and placing, opening or closing door or arranging object on the table, humans move in optimized manner with the combination of these three criteria. For example, placing an empty glass on the table, humans are tending to move in a minimum time and distance, but if the glass is full of water, the arm is required to move with minimum acceleration and in the shortest distance. For a robot hand to have these motion characteristics performing a specific task, similar approaches of motion generation need to be properly considered.

Initially, single objective function optimization using Genetic Algorithm (GA) has been considered by [1]-[3] for trajectory planning and collision avoidance. The motion generation of these works are based on direct kinematics of the robot manipulator, which is proven better than motion generated using inverse kinematics by [4]. A similar work by [5], proposed robot manipulator motion generation using virus evolutionary GA based on direct kinematics. Multi objective optimization using GA has been suggested by [6] in 1989 and since then, other researchers have been developing new methods such as multi objective genetic algorithm (MOGA) [7], non-dominated sorted genetic Algorithm (NSGA) and among other methods explained in [8]. In [9], multiple criteria are optimized for a two and three degree of freedom (dof) planar robot. The five selected objectives are; minimum joint traveling distance, minimum joint velocity, minimum Cartesian distance, minimum Cartesian velocity and minimum energy. A direct kinematics optimization using GA is adapted in [9].

Two multi objective evolutionary algorithm has been proposed by [10]. The motions of a Cartesian robot are generated using these two methods namely; non-dominated sorting genetic algorithm and multi-objective differential evolution. The robot arm has to move from a starting point to a goal position avoiding three obstacles simultaneously optimizing the travelling time and energy consumption. Liu et al. [11], proposed an improved version of non-dominated differential evolution (NSDE) to generate the planar robot manipulator motion. The arm motion not only follows the desired trajectory but also satisfying three different characteristic which are, singularity avoidance, obstacles avoidance and joint limit avoidance. MOGA is also proposed by [12] for generating motion of a three dofs parallel kinematics machine. The motion optimization is considering minimum electric energy used by the actuators, maximum torque and minimum shaking force. MOGA is chosen based on its robustness and effectiveness of the generated solutions. Most of these works are focused on motion generation of the robot hand on simulated environment and using planar type of robots.

In this paper, we propose an optimal robot arm motion using neural controllers satisfying three conflicting objectives; minimum execution time, minimum distance and minimum acceleration simultaneously. The advantage of the propose algorithm is the ability of MOGA to find multiple Pareto optimal solutions in a single run. Another advantage is that some neural controllers optimized all three objective functions simultaneously. In addition it covers a wide range of initial and goal position.

A new mobile humanoid robot platform has been developed in our laboratory. The actual joint angles are acquired directly from the developed robot and from these data, angular velocity, end effector velocity and acceleration are calculated. The joint angular velocities are used in the simulation and experiment to generate the kinematic properties of the robot hand.

Mobile Humanoid Robot

The developed mobile humanoid robot system is shown in Fig. 1(a) and a simulated version of the upper body has been developed in MATLAB environment as Fig 1(b). The key specifications of the mobile humanoid robot are:

- Arm length – 54 cm
- Total height – 134 cm
- Robot width – 52 cm
- Upper body weight – 14 kg
- Maximum moving speed 1 m/s

In general, the developed robot has fourteen degree of freedoms (dofs), five dofs on each arm, two simple grippers and two dofs head. The camera and a laser range sensor, *LR2* as in Fig. 1(a) are used for object recognition and position determination. The shoulder, upper arm and lower arm are actuated by three DC motors. Three servos are used for each hand for object grasping and simple manipulation. The detail explanation of the mechatronic design and kinematics analysis are presented in [13]. The upper body of the humanoid robot is placed on a moving platform actuated by two Yamaha AC motors to increase its mobility. For safe robot navigation the camera and laser range sensor, *LR1* are utilized to detect obstacles and humans.

Problem Formulation

In generating a robot arm motion, the speed, time and trajectory while performing daily activities must be properly considered in order to complete the task successfully. In each task, the main problem of motion generation will be the arm trajectory, the moving speed and the execution time from the initial to the desired goal position. There are infinite numbers of possible trajectories and motion velocities connecting these two points. The main problem is how to determine the joint trajectories in order to reach the goal position in minimum possible time or distance.

In order to find the optimal trajectories, we have developed a mobile humanoid robot and a robot arm simulator as shown in Fig. 1(a) and Fig. 1(b) respectively. The performance of the evolved neural controllers will be tested both in simulated environment and on the developed system. In this paper, the robot arm is required to move from an initial position to a goal position, as it placing an object on the table as in Fig. 1(b).

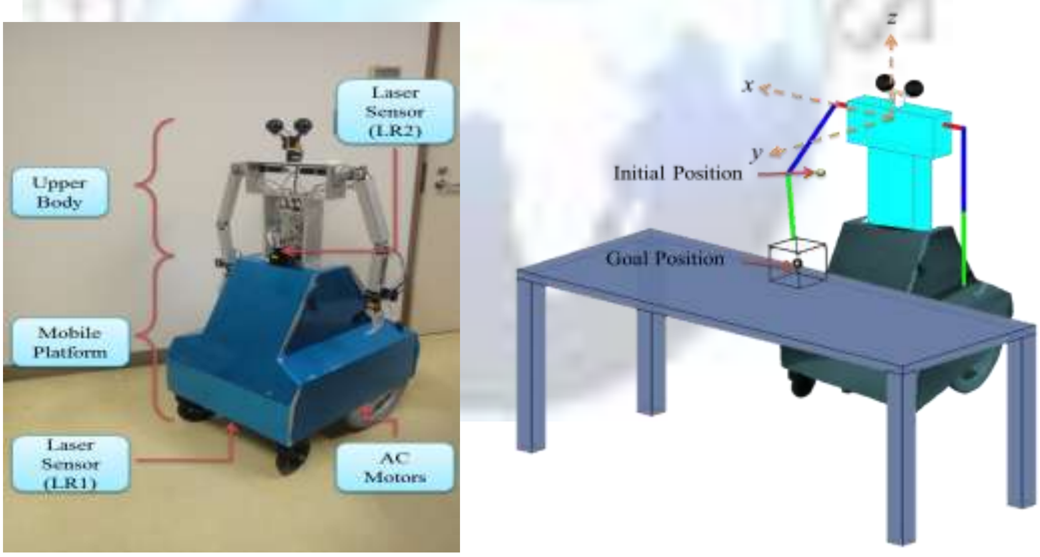


Figure 1. (a) The developed mobile humanoid robot (b) Robot simulation

Evolution of Neural Controllers

A. Feed Forward Neural Networks

In this paper, a feed forward neural networks (FFNN) is chosen for its simplicity and robustness compared to back propagation neural networks [14]. The performance of FFNN has been verified in our previous work [15] and suitable for our application. Fig. 2 show the single hidden layer FFNN, which receives three inputs: the difference between the robot hand and goal positions coordinate in x, y and z axis. The potentiometers reading of each joints are utilized in the inverse kinematics to determine the robot hand position [13]. In simulated environment, the goal position is pre-determined while in real situations is generated based on the image processing and laser sensor. The output units directly control the 3 DC motors used to move the shoulder, upper arm and lower arm. The output units use a sigmoid activation function where 0 to 0.5 is for one the motor moving direction and 0.5 to 1 for the opposite direction. The weight connections of the neural controller are optimized using genetic algorithm.

B. Multi Objective Genetic Algorithm (MOGA)

MOGA have proven to be well suited for optimization problem with multiple objectives. It becomes the method of choice for solving optimization problem that are too complex to solve using deterministic techniques such as Jacobian method. The main advantage of MOGA is they are able to gain a number of solutions in a single run [16]–[18]

In our work a non-dominated sorting genetic algorithm (NSGA) was employed to evolve the neural controller. The neural controller weight connections are encoded as real numbers. The performance of NSGA has a better performance than other MOGAs has been proven by [19]. Multiple Pareto optimal solutions can be successfully determined using NSGA. Before selection is performed, the population is ranked on the basis of domination using Pareto ranking. All non-dominated individuals are classified in one category with a dummy fitness value, which is proportional to the population size. After this, the selection, crossover, and mutation operators are performed. Details explanations on MOGAs are discussed in [20], [21].

Objective Functions

A. Minimum Execution Time (MT)

The first selected objective function is the minimum execution time. For a simple motion of the robot hand, such as moving freely or placing a small rigid object, this objective function is very significant. In our system, the sampling time to process the sensors data and send the motor command is 0.03 second. Therefore, the objective function is to minimize the number of step for the robot to reach the goal position as follows:

$$f_1 = n_{step} \tag{1}$$

B. Minimum Distance (MD)

For a more specific task, such as pushing a box, the trajectory connecting the initial and goal positions must be the shortest one. This is the reason minimum distance is selected to be one of the objective functions. The minimum distance objective function is shown as follows:

$$f_2 = \left| \sum rt_i - sd \right| \tag{2}$$

where Σrt_i is the summation of robot hand moving distance in each time step and *sd* is the shortest distance of the robot hand from its initial to the goal position.

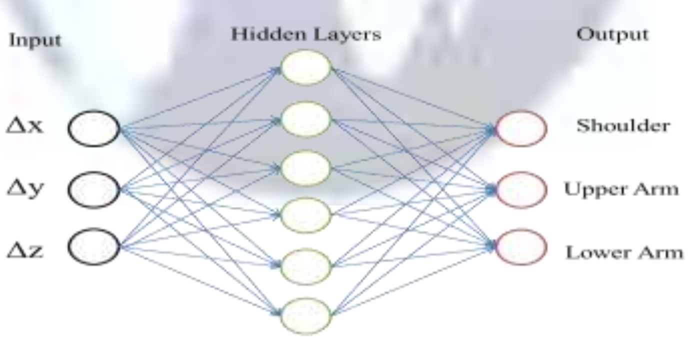


Figure 2. Feed forward neural network

C. Minimum Acceleration (MA)

If the case of a non-rigid object, such as placing a glass of water on a table, it will be better for the robot hand to move with minimum acceleration. A gradually increasing velocity from the starting position and gradually decreasing velocity toward the goal position are required for smooth motion. In this case, the total acceleration of the robot hand is minimized to have a constant velocity. Two penalty functions are also implemented in order for the robot to have a gradually deceleration before reaching the goal position and the number of velocity change for a smooth motion throughout the trajectories. Therefore, the minimum acceleration objective function is as follows:

$$f_3 = \sum a_{hand} + \left(v_{hand\_end} * w\right) + (nvc * w) \tag{3}$$

Where, Σa_{hand} is the summation of robot hand acceleration in each time step, v_{hand_end} is the robot hand velocity when it approaches the goal position, w is the weight function and nvc is number of velocity changes. The number of velocity changes is very important in order to minimize the rapid changes of the robot hand velocity in each time step. The weight function (w) is used to adjust the priority between Σa_{hand} ,v_{hand_end} and ncv. In the first motion generation, the value of w is set to be 1, and once the value of each term is known, w can be determined. In our implementation the value of w used is 60.

Results

The robot hand is required to move from an initial position to a goal position as it's placing an object on the table from a holding position. The performances of generated optimal neural controllers are tested in simulated environment and on the real robot. The Pareto front optimizing the three criteria as in (1), (2) and (3), are shown in Fig. 3(a). Twenty four individuals in Pareto set have been generated with maximum 80 iteration of the MOGA. Three individuals (NN1, NN2 and NN3) are chosen to be further discussed. The selection of these individuals is for comparing the performance of the optimal neural controller NN2 (one of the optimal solutions) with NN1 and NN3, which are prioritizing on two and single objective optimization respectively. NN3 is the extreme solution and very similar to single objective optimization which give priority to minimum acceleration objective function only (Fig. 3(b) and Fig. 3(d)).

Fig. 3(b) and Fig. 3(c) clearly show the performance of NN1 solution optimizing two objective functions, minimum time (f_1) and minimum distance (f_2). However, moving with a minimum time will make the robot hand moves faster and have a higher total acceleration (f_3) which is 30% more than NN2 and NN3 solutions. Fig. 3(b) and Fig. 3(d) show NN3 solution which is similar to a single objective optimization and only minimizing the total acceleration (f_3) of the robot hand motion. The robot hand completes the task 20% slower than NN2 and NN3. If all three criteria is a priority in generating the robot hand motion, NN2 perform the best. With a small difference in distance (f_2) and time (f_1) compare to NN1, NN2 has lower total acceleration (f_3) thus having a smoother motion and suitable for a task that required high stability and accuracy.

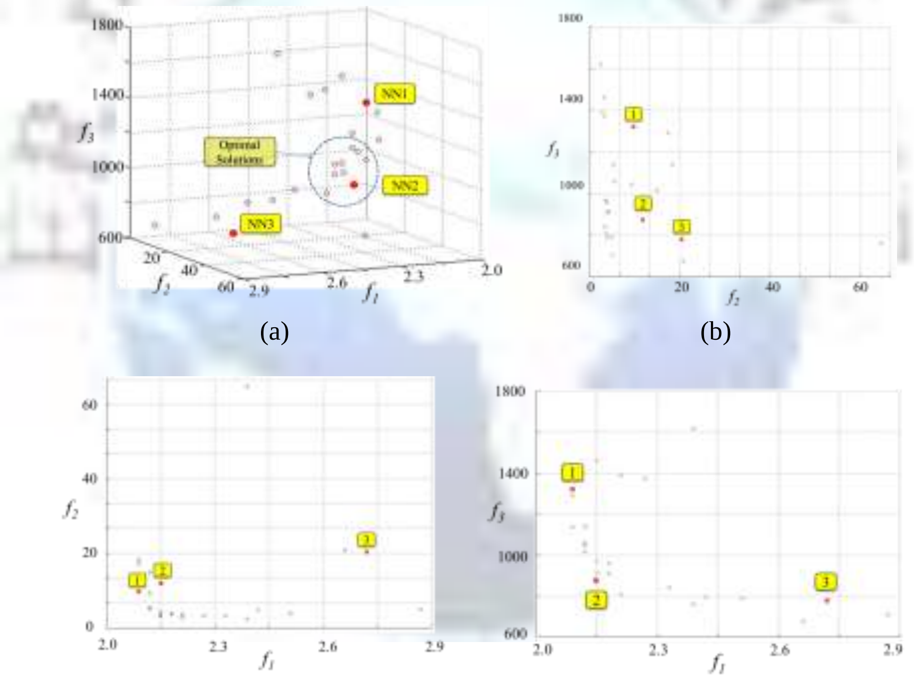


Figure 3. Pareto front of MT-MD-MA objective functions in (a)Isometric view (b) f_2-f_1 view (c) f_3-f_1 view (d) f_3-f_2 view

Fig. 4 shows the simulated motion generated using NN1, NN2 and NN3 solutions. The trajectory for NN1 and NN2 are improved compared to NN3. The robot hand move closer to the shortest distance for NN2 and NN1 solution compared to NN3 objective function where the robot hand move slightly away from the shortest trajectory to reach the goal.

The performance of the generated neural controllers is further tested on the real robot. The video capture of the experiment with the humanoid mobile robot for NN1, NN2 and NN3 are shown in Fig. 5(a), Fig. 5(b) and Fig. 5(c) respectively. The generated motion satisfying all three objective functions can be clearly differentiate and visualized. Fig. 6(a), Fig. 6(b) and Fig. 6(c) show simulation results of the joint angular displacement for shoulder (θ_1), upper arm (θ_2) and lower arm (θ_3) respectively. The performance is compared with the joint angular displacement acquired from the real robot as in Fig. 6(d), Fig. 6(e) and Fig. 6(f). The neural controllers show good performance in both environments but show some difficulties in maintaining a straight line trajectory and it can be visualize when the robot is in motion.

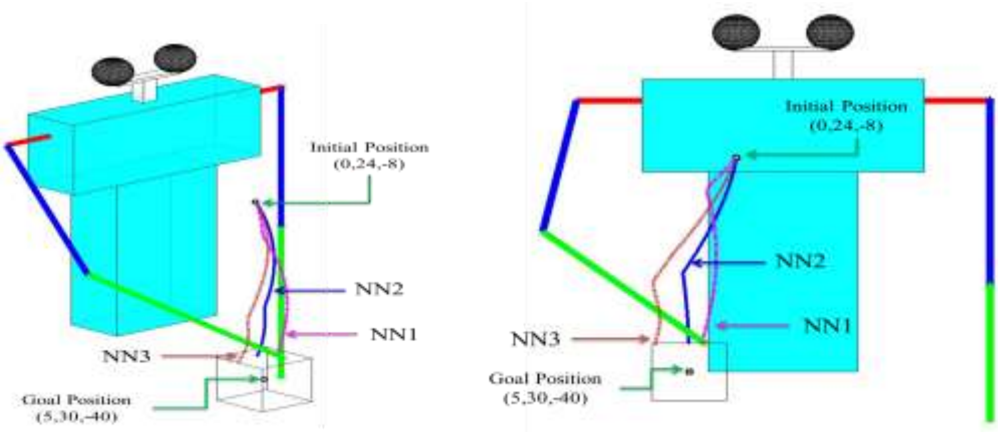
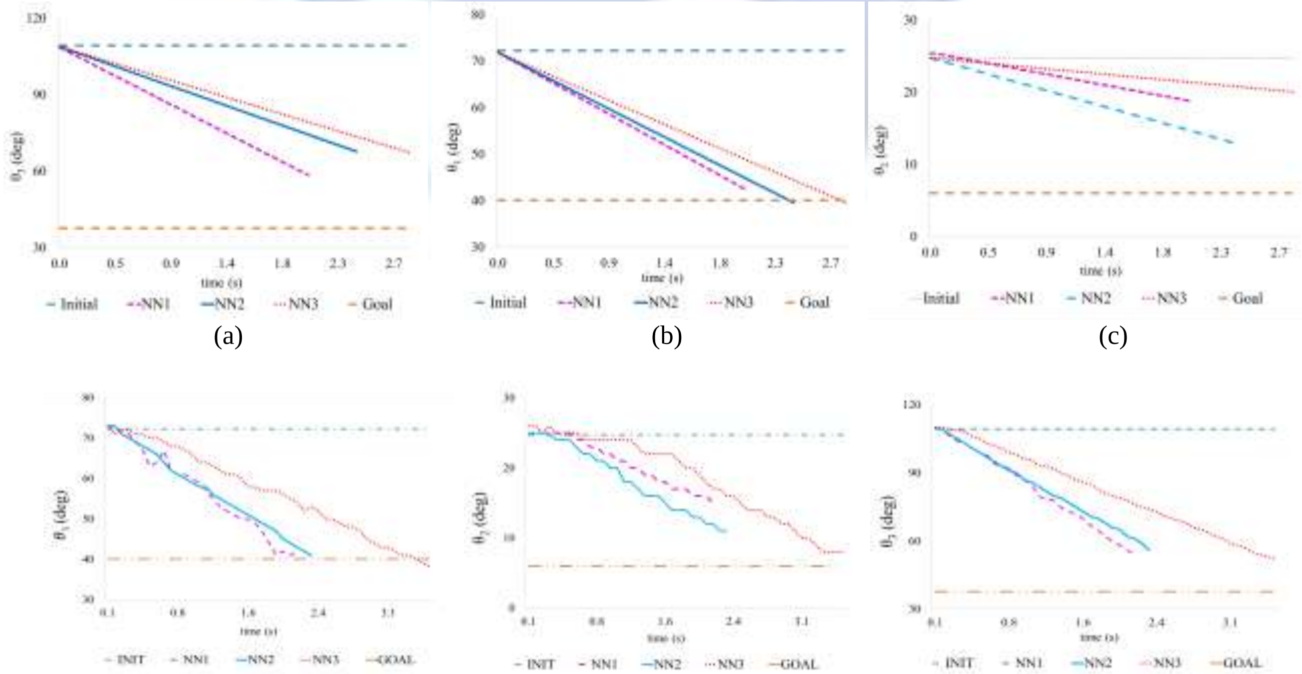


Figure 4. Robot hand motion for NN1, NN2 and NN3.

(a) (b) (c)

Figure 5. Video capture of robot hand motion for (a) NN1 (b) NN2 (c) NN3



(a) (b) (c)

(d) (e) (f)

Figure 6. Joint angular displacement of the robot arm (a) θ_1 simulation (b) θ_2 simulation (c) θ_3 simulation (d) θ_1 experiment (e) θ_2 experiment (f) θ_3 experiment

Conclusion

In this paper, we proposed a MOGA based method for humanoid robot arm motion generation. The MOGA generated optimal solutions regarding the three selected objective functions. The results showed that the optimal solution of MOGA neural controllers generated a much better motion trajectory, satisfying multiple criteria, simultaneously. Obstacles avoidance in Cartesian space, randomized initial and goal position will be considered in our future work.

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Biographies

Zulkifli Mohamed received B.E. degree from Universiti Teknologi MARA, Malaysia, in 2003 and M.E from Universiti Teknologi Malaysia, in 2006. He worked as a Lecturer in Universiti Teknologi MARA, Malaysia and currently working towards the Ph.D. in Toyama University, Japan. His research interests include mobile humanoid robots and intelligent robot. He is a student member of IEEE.

Mitsuki Kitani received the B.E. in 2008, M.E. in 2010, and Ph.D. in 2013 all from the Kagawa University. From April 2013, he is an Assistant Professor at the Faculty of Engineering, University of Toyama. From April 2011 to March 2012, he was a Research Fellow of the Japan Society for the Promotion of Science. His research interests are in sound signal processing and intelligent systems.

Genci Capi received the B.E. degree from Polytechnic University of Tirana, in 1993 and the Ph.D. degree from Yamagata University, in 2002. He is currently a Professor in the department of Electrical and Electronic Systems Engineering, University of Toyama. His research interests include intelligent robots, BMI, multi robot systems, humanoid robots, learning and evolution.