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Adaptive Humanoid Robot Arm Motion Generation by Evolved Neural Controllers

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Abstract **-** In this paper, we present a new method for humanoid robot arm motion planning satisfying multiple constraints. In our method, the humanoid robot arm motion generation is formulated as an optimization problem. Four different constraints, which cover a wide range of humanoid robot tasks, are considered: minimum time, minimum distance, robot hand acceleration and constant joint angular velocity. Results show that arm motions have different characteristics. In order to further verify the performance of humanoid robot arm motions, they are transferred in humanoid robot mobile platform.

Keywords**:** Humanoid mobile robot, Motion planning, Neural networks, Genetic algorithms.

1. Introduction

Humanoid robots are expected to perform in everyday life environments. Therefore, they have to perform a wide range of tasks, such as picking an object and giving it to the human, removing an unnecessary object etc. The wide range of robot task requires different robot motion strategies. For example, the speed of moving the hand to the glass of water is usually higher then moving the hand with the glass of water. In addition, because there are an infinite number of trajectories connecting the robot hand position with the goal location, the robot has to select the best trajectory and speed in order to complete the task successfully.

A lot of work has been done on humanoid robot arm motion generation. Flash and Hogan (1985) had proposed minimum hand jerk criteria, Rosenbaum et al. (1995) proposed minimum angle jerk criteria and minimum torque change criterion introduced by Uno et al. (1989), where control objects are the joint links plan in an intrinsic dynamic- mechanical space. Nakano et al. (1999) had proposed minimum commanded torque change criterion and using representation of motor commands controlling the muscles. Wada et al. (2001)had proven that the minimum commanded torque change is the closest to human trajectories.

In other studies, Vahrenkamp et al. (2008) suggested Rapid-Exploring Random Trees (RRTs) which can adapt the number of degree of freedom used in robot motion thus improving the performance and quality of the trajectories. The numbers of degree of freedom used are optimized using RRT. In an eight degree of freedom robot, RRT determines the optimum number of joints needed to complete the task. Ang et al. (2009) proposed a minimum time motion planning of robot arm using Pareto based multi-objective Bees Algorithm for a SCARA robot. Four different operators are used to optimize the cubic splines trajectories thus minimizing the travelling time of the robot which are discrete recombination, intermediate recombination, line recombination and path redistribution and relaxation. However, most of the previous works are focused on understanding human arm motion generation criteria.

In our work, we propose a humanoid robot arm motion generation method based on four different criteria. The four criteria are minimum time, minimum distance, robot hand acceleration and constant

joint angular velocity. In our method we evolved a neural network that generates the best robot motion for each objective function. These four criteria cover a wide range of robot motion required during everyday life robot tasks. Therefore, the selection of the best criteria to generate the trajectory is based on the taskthe robot has to perform. Another advantage of our method is that we employ a single neural controller for each objective function to generate the robot arm motion in a wide range of initial and goal location. These different criteria will make the robot more intelligent when choosing the best objective function for the given task. In addition, a new mobile humanoid robot platform has been developed to verify the performance. The robot composed by the upper part body and a mobile platform for navigation.

The paper is organized as follows. In section II the mobile humanoid robot specification are presented. The robot arm motion generationis discussed in section III. In section IV and section V, the neural controller and the evolution of neural controller are explained. The simulation and experimental results are provided in section VI. In the last section, we give conclusions and future works.

2. Mobile Humanoid Robot

T The mobile humanoid robot has been developed in our lab is shown in Fig. 1. The key performance specifications of the mobile humanoid robot are:

- Arm length – 54 cm
- Total height – 134 cm
- Maximum moving speed 1m/s

In general, the developed robot has fourteen degree of freedom, five degree of freedom on each arm, two hands and two degree of freedom head. The humanoid robot is placed on a moving platform to increase its mobility.The camera and a laser range sensor are used for safe robot navigation. The shoulder, upper arm and lower arm are activated by three DC motors. Three servos are used for each hand for object grasping and manipulation. Two web cameras are used for mobile platform motion and object recognition. The detail explanation of the inverse kinematics and mechatronic design are presented by Mohamed et al. (2012).

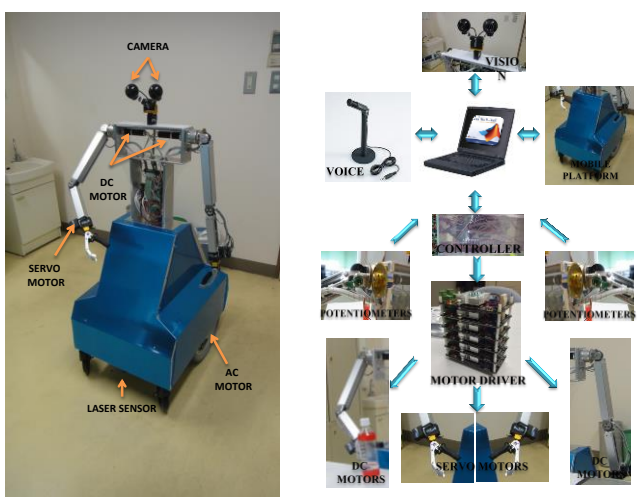


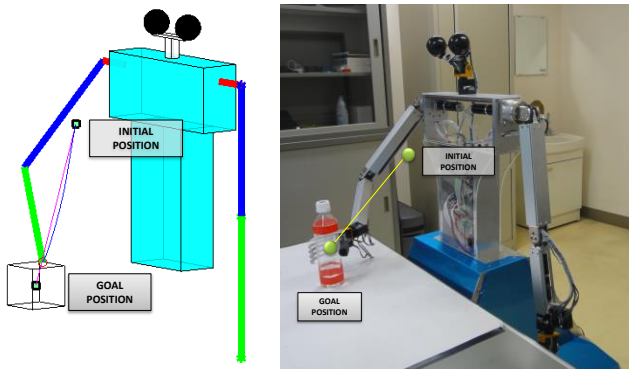
Fig. 1. Developed robot.

3. Robot Arm Motion Generation

Picking and placing, removing, pushing, etc. in all these tasks the humanoid robot trajectory and speed must be carefully selected in order to complete the task successfully. Therefore, in each stage of task performance, the main problem is what trajectory and how the moving speed must change connecting the robot hand and goal positions.

The humanoid robot has to move the hand (object) from the initial to the goal position, which is connected with an infinite number of trajectories and motion velocities. In order to find the optimal

trajectories, we have developed a robot arm simulator (Fig. 2(a)), which replicates the motion of the real robot (Fig. 2(b)).



(a) (b)

Fig. 2. (a) Simulation setup (b) experimental setup.

4. Neural Controller

Neural networks (NN) are mathematical model that is inspired by the biological neural networks. It is a set of algorithms for optimization and consists of links, interconnected state variables, weight values associated with each links and a transfer function. Feedforward neural networks are the most widely used in many practical applications. It has been chosen for its simplicity and robustness compare to backpropagation neural networks which has some drawback if the complexity of the data is increasing (Montana et al. (1989)).

In our work, we consider a single hidden layer feedforward neural network (FFNN), as shown in Fig. 3. The FFNN receives three inputs: the difference between the robot hand and goal positions coordinate in x, y and zaxis. The inverse kinematics,based on potentiometer readings, is utilized to determine the current position of the robot hand. In simulated environment, the goal position is pre-determined while in real situations is generated based on the image processing. 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 motor moving direction and 0.5 to 1 for the opposite direction. The weight connections of the neural controller are trained using genetic algorithm.

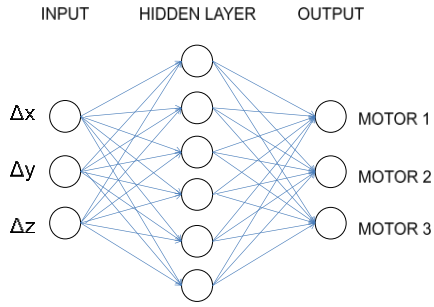


Fig. 3. Feedforward Neural Networks.

4. Evolution of Neural Controllers

4. 1. Genetic Algorithm

Genetic algorithms (GAs) are adaptive heuristics and global searching technique based on the principle of evolution (Montana and Davis (1989)). The two basic processes of GAs are inheritance and competition toward better region of search space.

In our work, we used an extended multi-population genetic algorithm, where the subpopulations apply different evolutionary strategies (Capi and Doya (2005)). In addition, the

subpopulations compete and cooperate among each other. The GA parameters used are shown in Table 1.

Table 1. Summary of Genetic Algorithm Parameters

Number of Subpopulation	3
Number of Individuals	450, 450, 300
Maximum Generations	80

4. 2. Fitness Functions

4. 2. 1. Minimum Time

The first criterion is the minimum time taken for the robot hand to move from its initial position to the goal position. This objective function is very significant in everyday life environments where the robot hand has to move freely from one point to the other, or move small rigid objects. 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.

$$f = number\ of\ step \tag{1}$$

4. 2. 2. Minimum Distance

For a specific task, such as drawing a straight line, arranging books and pushing an object, the trajectory connecting the initial and goal positions must be the shortest one. This is the reason minimum distance in selected to be one of the objective functions. The minimum distance objective function is as follows:

$$f = abs(\sum rt_i - sd) \tag{2}$$

where$\sum rt_i$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 position to the goal

4. 2. 3. Robot Hand Acceleration

If the object is not rigid, such as a cup of coffee, it will be better to move with minimum acceleration. The robot hand will have a gradually increasing velocity from the starting position and gradually decreasing velocity toward the goal position.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 changefor a smooth motion throughout the trajectories. Therefore the minimum acceleration objective function is as follows:

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

where$\sum a_{hand}$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 $\sum a_{hand}$and v_{hand_end}. In our implementation the value of *w* used is 100

4. 2. 4. Constant Joint Angular Velocity

Another way to minimize the change in hand moving velocity is by minimizing the joint angular acceleration. Therefore, the following fitness function is also considered:

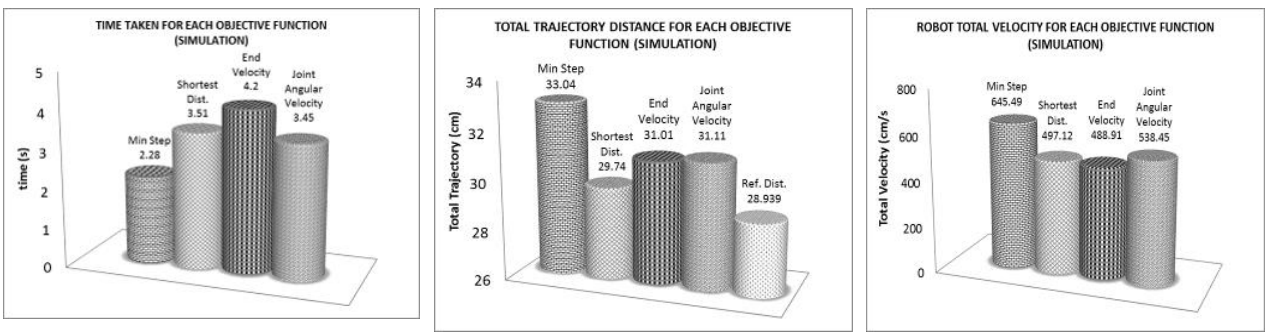
$$f = \sum \alpha_1 + \sum \alpha_2 + \sum \alpha_3 \quad (4)$$

where ,α_1, $\alpha_2$andα_3, is the robot angular acceleration for shoulder, upper arm and lower arm respectively

5. Results

5. 1. Simulation Results

The performance of the best neural controller generated for each objective function is shown in Fig. 4. Fig. 4(a) shows that minimum time neural controller reached the target position very fast (2.28second). However, the hand acceleration (Fig. 4(b) is really high, making it not suitable for tasks such as moving a glass of water. An interesting result is that the minimum time and minimum distance trajectories are very different. The minimum time neural controller reached the goal position following the longest trajectory. Because the change in the hand velocity is included as a penalty function in minimum distance and minimum angular acceleration, Fig. 4(c) shows that there is not too much change in the fitness with minimum acceleration of the robot hand. The total velocity for the whole trajectory is 488.91 cm/s. The performance of constant joint angular velocity criterion is slightly lower with 538.45 cm/s. These simulations results show that all four criteria perform accordingly to their objective functions.

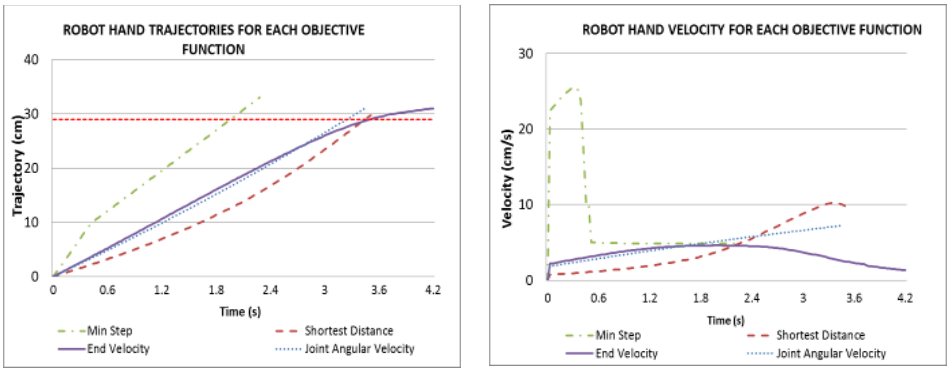


(a) (b) (c)

Fig. 4. (a) Time to the goal (b) total trajectory distance (c) total velocity.

Fig.5(a) and Fig. 5(b)show the robot hand trajectories and velocity profile for each objective function. From the velocity profile, minimum step criterion has the lowest stability in the motion due to high velocity within 1 second from its initial position. Other three criteria had a low initial velocity, which increases gradually. Theminimum acceleration of the robot hand generated the robot motion which reaches the goal position with a small velocity compared to other objective function.

These objective functions have their own advantages and disadvantages over each other. If the robot hand need to move fast, the minimum time is best solution, for stability, robot hand acceleration and constant joint angular velocity can be used. For high accuracy, shortest distance will be the best objective functions. These results will be used in the next step of this research by implementing these criteria as the multi objective functions of the robot and it will choose the best objective function for a given command or task.



(a) (b)

Fig. 5. Robot hand (a) trajectory (b) velocity.

5. 2. Experimental Results

The video capture of the experiment with the humanoid mobile robot is shown in Fig. 6. The robot has to place the bottle of water on the table. Because its initial position is far from the table, first the robot utilizes the laser and camera sensors data to reach the table. The robot arm motion is generated by four optimal neural controllers in order to compare the performance. The same motion is also repeated without holding the bottle to compare the results.

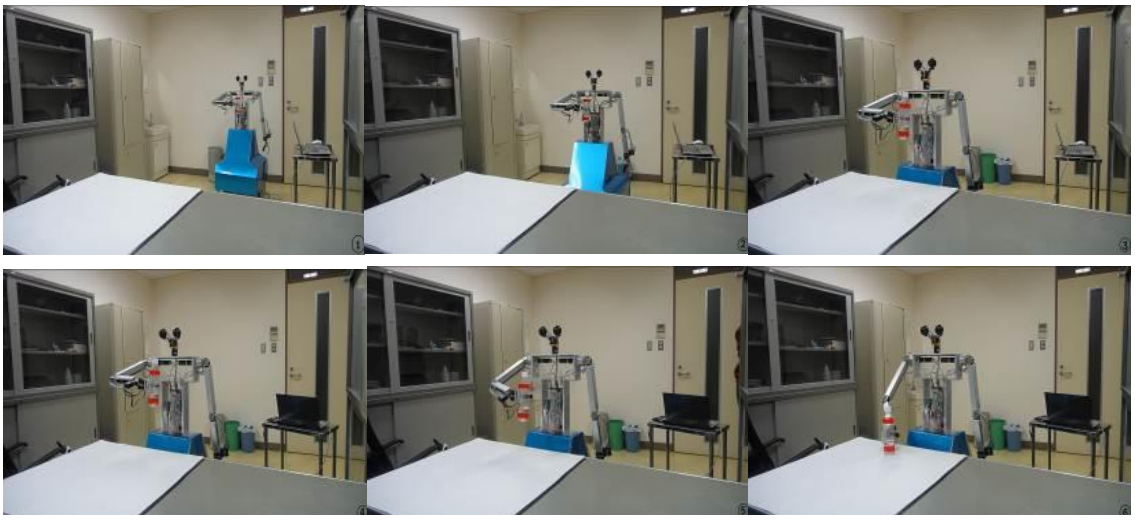
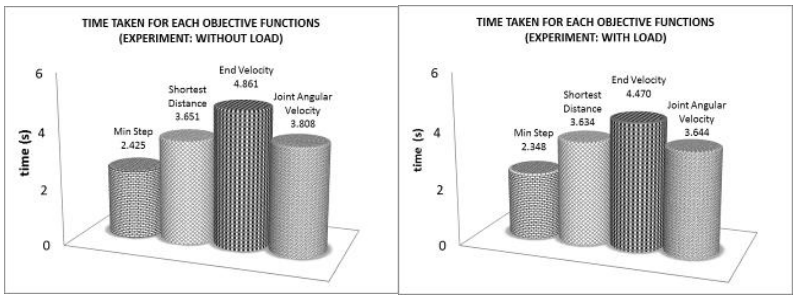


Fig. 6. Video capture of the experiment.

The time needed to reach the table is shown in Fig. 7(a) for no bottlemotion and Fig. 7(b) with the bottle motion. In simulation the minimum time taken was 2.28 second, while in the real robot it took 2.425 second no bottle and slightly different (2.38second)with the bottle. The same results are obtained also for the other three criteria. The performance of the robot manipulating the bottle is comparable with the simulation results.



(a) (b)

Fig. 7. Time to the goal (a) without load (b) with load.

The comparison between the simulation and two experimental setups (with and without bottle) are shown in Fig. 8. In simulation, the external conditions are not considered such as joint friction, mechanical gear backlashes, motor gearhead backlashes, gravitational effect, mechanical design and the movement of the water inside the bottle. In the experiment, these factors are affecting the performance of the robot. In terms of time taken, there are small differences for all objective functions. It can be seen that the motion is slightly faster while holding the bottle due to higher gravitational force.

These external factors affect the performance of the robot, as shown in Fig. 9. All three angles of the right hand are measured and compared. In simulation, the trajectory and the angle movement of each joint are very smooth. Although the performance of the robot is not as good as the simulations while holding the bottle, the robot follows nearly the same trajectory generated in the simulated environment

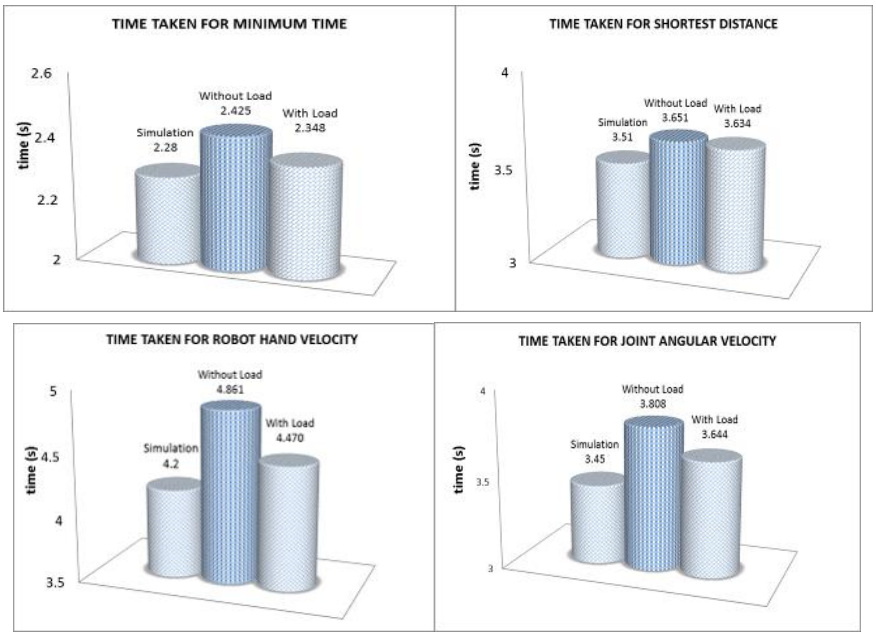
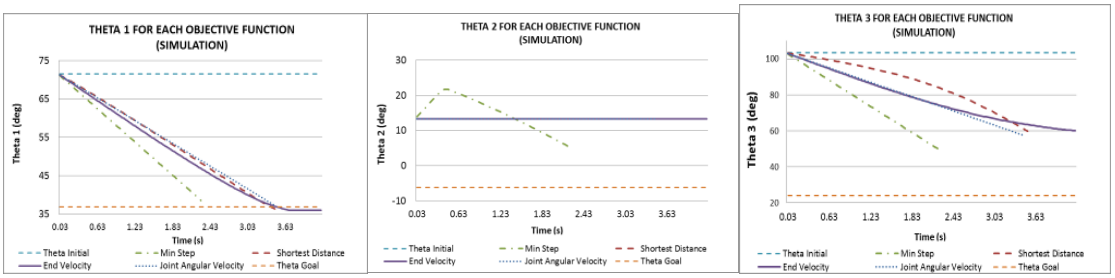
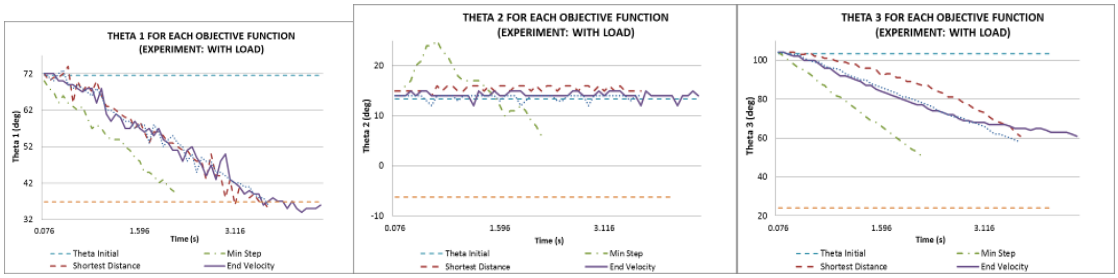


Fig. 8. Comparison between objective functions.



(a)



(b)

Fig. 9. Comparison between objective functions (θ_1, θ_2,&θ3) (a) simulation (b) experiment (with load).

6. Conclusion

This paper proposed four different criteria for robot arm motion generation. We evolved one optimal neural controller for each fitness function by using the genetic algorithm. The advantage of the proposed algorithm is that the robot can generate the hand motion by the best neural controller based on the task it has to complete. In addition, the same neural controller can be employed to generate to robot hand motion for different initial and goal positions. The simulation results were also tested in real robot hardware, resulting in a good performance.

In the future, we plan to employ multi-objective evolutionary algorithm for evolution of neural controllers. In addition, both arm motion generation will be considered.

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