Engineering Applications of Artificial Intelligence 22 (2009) 329–342

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

# Evolutionary multi-criteria trajectory modeling of industrial robots in the presence of obstacles

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ARTICLE INFO

*Article history:*
Received 15 October 2007
Received in revised form
11 April 2008
Accepted 10 June 2008
Available online 28 August 2008

*Keywords:*
Multi-objective optimal trajectory modeling
Obstacle avoidance
Elitist non-dominated sorting genetic algorithm (NSGA-II)
Multi-objective differential evolution (MODE)

ABSTRACT

Optimal trajectory planning for robot manipulators is always a hot spot in research fields of robotics. This paper presents two new novel general methods for computing optimal motions of an industrial robot manipulator (STANFORD robot) in presence of obstacles. The problem has a multi-criterion character in which three objective functions, a maximum of 72 variables and 103 constraints are considered. The objective functions for optimal trajectory planning are minimum traveling time, minimum mechanical energy of the actuators and minimum penalty for obstacle avoidance. By far, there has been no planning algorithm designed to treat the objective functions simultaneously. When existing optimization algorithms of trajectory planning tackle the complex instances (obstacles environment), they have some notable drawbacks viz.: (1) they may fail to find the optimal path (or spend much time and memory storage to find one) and (2) they have limited capabilities when handling constraints. In order to overcome the above drawbacks, two evolutionary algorithms (Elitist non-dominated sorting genetic algorithm (NSGA-II) and multi-objective differential evolution (MODE) algorithm) are used for the optimization. Two methods (normalized weighting objective functions method and average fitness factor method) are combinedly used to select best optimal solution from Pareto optimal front. Two multi-objective performance measures (solution spread measure and ratio of non-dominated individuals) are used to evaluate strength of the Pareto optimal fronts. Two more multi-objective performance measures namely optimizer overhead and algorithm effort are used to find computational effort of NSGA-II and MODE algorithms. The Pareto optimal fronts and results obtained from various techniques are compared and analyzed.



## 1. Introduction

The design of engineering systems involves simultaneous consideration of multiple criteria or objectives. Some of these objectives will be in conflict often. Thus, a trade-off exists, which can be investigated by using multi-objective optimization methods. In such a problem, no single optimal solution exists; rather there is a set of equally valid optimal solutions known as the Pareto optimal set. The solutions in this set show the designer what is possible and allow him to make a fully informed choice.

The goal of robot systems is to do tasks at a cost as low as possible. Thus, the minimum-cost trajectory planning in the two-stage realization of manipulators control (i.e., planning first and tracking next) is an important effort to accomplish the goal. A large number of robotic applications involve repetitive processes. This technological characteristic justifies offline trajectory planning.

In order to maximize the speed of operation that affects the productivity in industrial situations, it is necessary to minimize the total traveling time of the robot. More research works have been carried out to get minimum time trajectories (Shiller and Dubowsky, 1991).

Planning the robot trajectory using energy criteria provides several advantages. It yields smooth trajectories easier to track and reduce the stresses of the actuators and of the manipulator structure. Moreover, saving energy may be desirable in several applications, such as those with a limited capacity of the energy source (e.g., robots for spatial or submarine exploration). Examples of energy optimal trajectory planning are provided in some literatures. Both optimal traveling time and the minimum mechanical energy of the actuators are considered together as objective functions in some literatures (Saramago and Steffen, 1998, 1999, 2001 and Chettibi et al., 2004). Saramago and Steffen (2001) used sequential unconstrained minimization techniques (SUMT) to do optimum trajectory planning of an STANFORD

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doi:10.1016/j.engappai.2008.06.002

**Nomenclature**

$J$ robot joint number
$m$ knot number of the robot joint trajectory
$K_1$ robot joint trajectory in the workspace
$K_2$, $K_3$ and $K_4$ obstacles
$z_1$ traveling time of the robot
$z_2$ mechanical energy of the robot actuators
$z_3$ penalty for obstacle avoidance
$\dot{q}$ generalized robot joint velocity
$\ddot{q}$ generalized robot joint acceleration
$D_{ij}$ inertial system matrix of the robot
$C_{ijk}$ coriolis and centripetal forces matrix
$G_i$ gravity loading vector,
$J_i$ moments of Inertia of robot
$\bar{r}_i$ center of mass of robot links
$g$ acceleration due to gravity with respect to the base coordinate system
$T$ traveling time of robot end effector from initial configuration to final robot configuration
$u_i$ generalized forces
$QC_j$ maximum displacement of robot joint $j$
$VC_j$ maximum velocity of robot joint $j$
$WC_j$ maximum acceleration of robot joint $j$
$JC_j$ maximum jerk of robot joint $j$
$UC_j$ maximum force/torque of robot joint $j$
$I$ set of possibly colliding pairs of parts
$h\varepsilon R^m$ design variables (time intervals) for strategy 1
$\gamma$ B-spline coefficients (variables) in strategy 2
$t_1 < t_2 \cdots < t_{m-1} < t_m$ an ordered time sequence
$h_i = t_{i+1} - t_i$ time interval
$T = \sum h_i$ total time
$\dot{q}_1, \dot{q}_m$ and $\ddot{q}_1, \ddot{q}_m$ robot joint velocities and accelerations at the initial time $t_1$ and terminal time $t_m$
$\gamma_j^i$ B-spline coefficients

manipulator. The objective functions used in optimal trajectory planning are minimum traveling time, minimum mechanical energy of the actuators and minimum penalty for obstacle avoidance. The limitations of their work are: (1) They have approached the problem as a single objective optimization problem (all objectives are combined as a single objective function using weightage objective function method). (2) If the user does not know the weightage to be given for each objective, their approach is not applicable. (3) The method used by them cannot be used for treating multi-objectives simultaneously. (4) They got only one optimal solution. But for a real world problem, a Pareto optimal front that offers a good number of optimal solutions for user's choice is most desirable and (5) SUMT is a conventional optimization technique and hence a global solution may not be possible.

The methods that are used in the literatures such as dynamic programming (Shiller and Dubowsky, 1991), SUMT (Saramago and Steffen, 1998, 1999, 2001) and sequential quadratic programming (Chettibi et al., 2004) to tackle the complex instances (obstacles environment) have some notable drawbacks viz.: (1) they may fail to find the optimal path (or spend much time and memory storage to find one) and (2) they have limited capabilities when handling constraints. For example, the robot joint acceleration and deceleration may not be within their maximum limits. To overcome the above drawbacks, the evolutionary algorithms can be used. The advantages of evolutionary techniques are: (1) They are population based search. So a global optimal solution is possible. (2) They do not require any auxiliary information like gradients, derivatives, etc. (3) Complex and multimodal problems can also be solved for global optimality. (4) They are problem independent techniques, i.e., suitable for all types of problems.

In the last 20 years, evolutionary algorithms such as multi-objective genetic algorithm (MOGA) (Fonseca and Fleming, 1995), Elitist non-dominated sorting genetic algorithm (NSGA-II) (Deb et al., 2002), multi-objective differential evolution (MODE) (Babu and Anbarasu, 2005), Niched Pareto genetic algorithm (NPGA) (Horn et al., 1994), among many other variants (Coello and Carlos, 1999) have been applied in a plethora of fields such as control, system identification, robotics, planning and scheduling, image processing, pattern recognition and speech recognition (Bäck et al., 1997). Evolutionary techniques for multi-objective optimization are currently gaining significant attention from researchers in various fields due to their effectiveness and robustness in searching for a set of trade-off solutions. Unlike conventional methods that aggregate multiple attributes to form a composite scalar objective function, evolutionary algorithms with modified reproduction schemes for multi-objective optimization are capable of treating each objective component separately and lead the search in discovering the global Pareto optimal front.

Intelligent optimization algorithms such as NSGA-II and MODE are very much needed for trajectory planner of an intelligent real world robot. Since trajectory planning for a real world robot is a very complex and tedious task. This is due to the following reasons:

1. The planning algorithm has to consider the dynamic model of the robot. The dynamic model is depending on traveling time, payload and robot's task. It is a time-dependent one.
2. In robot's workspace, all types of obstacles (fixed, moving and oscillating obstacles) may be present. This calls for the planning algorithm to consider all types of obstacles for obstacle avoidance. Further, the information about the obstacles may be partially or fully unknown. Therefore, the obstacle avoidance checking is a very complex and time-dependent one.
3. The environment around the robot is an ever-changing one. This calls for the planning algorithm to update the details for trajectory planning for each time instant.

In this paper, two evolutionary algorithms namely NSGA-II and MODE are proposed to obtain optimal trajectory planning for an industrial robot (STANFORD Robot). The result of a multi-objective optimization is a Pareto optimal front, which is a set of competing solutions. However, the design implementation for a real-time problem will require a single solution. Two methods (normalized weighting objective functions method and average fitness factor method) are combinedly used to select best optimal solution from Pareto optimal front. Two multi-objective performance measures namely solution spread measure (SSM) and ratio of non-dominated individuals are used to evaluate the strength of Pareto optimal fronts. Two more multi-objective performance measures namely optimizer overhead and algorithm effort are used to find the computational effort of NSGA-II and MODE algorithms. This research work considers all the important decision criteria for the optimal trajectory planning of industrial robot manipulators, including the obstacle avoidance criteria for the obstacles and also incorporates information vagueness (Fuzziness).