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Multi-objective Design Optimization of the Robot Grippers with SPEA2

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Abstract: Robot grippers are the tools used for gripping, moving and fixing objects. They are integrated into robotic systems and can grip an object for at least one maneuver without any damage. Design optimization of robot grippers is crucial to carry on their dedicated jobs without any faults. The design optimization of robot grippers is a research topic. Robot grippers were optimized by using various methods for different aims in previous studies. In this study, it is aimed to optimize both the fluctuation of the power applied to an object by a gripper and the power transfer rate between actuator and ends of a gripper. Strength Pareto evolutionary algorithm II (SPEA-II), which is a multi-objective optimization method, has been applied to the problem for this aim. The experimental results were compared to the result of the previous studies. SPEA-II has better performance to the competitor as the comparison.

Keywords: *Engineering Optimization, Multi-objective Optimization, Robot Grippers, SPEA2*

1. Introduction

Robot grippers are the mechanisms used in industrial systems commonly. Robot grippers, used as tip component of robotic systems, are benefited in many fields such as assembly and welding processes, moving of pieces, holding of radioactive matters etc. Gripping an object has become a research topic as the importance of optimization studies has been increasing in industrial systems [1].

Design optimization of robot grippers is a necessity to perform their dedicated jobs without any faults. Various studies were conducted with different methods to detect optimal design in literature. The study conducted by Cutkosky[2] involving in selection, modelling and, designing of the grippers is the first study on optimization of robot grippers. Cutkoksky proposed an expert system to solve the gripping issues in the study.

Design optimization of robot grippers was formulated as a nonlinear optimization problem by Osyczka at first [10]. Osyczka et. al [3] proposed a robot gripper design based on multi-objective optimization. They applied a multi-objective genetic algorithm on different configurations of robot grippers. The best known values in literature were obtained as a result of the study. Saravanan et al. [11] applied three optimization methods (MOGA, NSGA-II and MODE) to three different robot gripper configurations. Datta and Deb [12] studied on two different gripper configurations and solved the problem by using NSGA-II. The objective functions of the studies [11-12] are the same as the ones defined by Osyczka in [10]

Lanni and Ceccarelli[4] dealt with the optimum design of grasp mechanism of the grippers with two-fingers. They aimed to optimize the kinematic design of a gripper mechanism along with to improve the time of the solutions. As a result of the optimization on the proposed mathematical model, they obtained better operating and structural features than the ones of the similar studies.

Cabrera et. al [5] carried out a design optimization for a multi proposed and multi-hand planer mechanism. Zitar et. al. [6] utilized single objective ant colony optimization to provide gripping solid objects with minimum power. Li et al [7] benefited from genetic algorithm to optimize link lengths and joint angles of robot grippers. Designs of small and large scale grippers were obtained with the best-known values at the end of the study.

Rao et al. [1] proposed a novel method named as teaching–learning-based optimization (TLBO). They applied the method to the well-known mechanical design problems as well as the robot gripper problem as a benchmark problem. The obtained results of the method were compared to the results of the population-based optimization methods in the literature. It was put forward that TLBO is more efficient than the competitors.

Dao et al. [8] approached to the design of a gripper with two flexible components as a multi-objective optimization problem. Fuzzy Taguchi method based on fuzzy logic was applied to the problem in the study. Two parameters were assigned to stand for horizontal and vertical powers as input values. These parameters were formalized with two objective functions: torque of torsional spring and the stress. The best known horizontal and vertical power values obtained as a result of their study.

Ciocarlie et al [9] studied on the design of a tendon-driven robotic gripper carried out a fingertip and enveloping grasps. The researchers optimized the parameters of springs providing the route of the active tendon and the passive extension powers. The best-known design with the parameters of the optimized tendon dimensions and activation was obtained.

In this study, a balanced gripping is aimed by optimizing the fluctuation of the power applied to object by the grippers and the power transfer rate between actuator and end of a gripper. The configuration of the gripper, objective functions and constraints in the study [3] were taken into account. SPEA2 was applied to the problem for the first time. Comparative results show that SPEA2

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is superior to the methods applied to the problem in the previous studies.

This paper is organized as follows. Section 2 describes SPEA2 and its adaptation to the problem. Section 3 presents experimental results and comparations with similar studies. Section 4 provides conclusions and suggestions about future studies.

2. SPEA2

Zitzler brought about SPEA in 1999. The algorithm was improved by Zitzler et al. in 2001 and renamed as SPEA2. SPEA2 is one of the multi-objective evolutionary algorithms developed to detect Pareto optimal solutions. The cases of the algorithm are presented in Fig.1

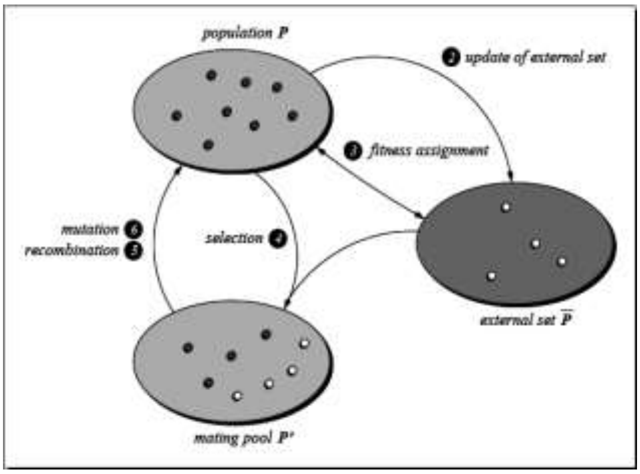

Fig. 1. Operation of the SPEA2 Algorithm[13]

The operation of the algorithm is summarized in Fig. 2:

Input: *N(population size), N'(archive size), T(maximum number of generations)*
Output: *A(nondominated set)*
$P_0 \leftarrow$ *InitializationPopulation(N)*
$P'_0 \leftarrow \{\}$
While(*t>T*)
    FitnessPopulation←FitnessAssigment(P_t)
    FitnessArchive←FitnessAssigment(P'_{t+1})
    $P'_{t+1} \leftarrow$ *ExtractNonDominatedSolution*(P_t, P'_{t+1})
  If (size(P'_{t+1}) > N')
    $P_{t+1} \leftarrow$ *Reduction_Size*(P_{t+1})
  ElseIf
    $P'_{t+1} \leftarrow$ *FillOutNonDominatedSolution*(P_t, P'_{t+1})
  End
    Selected←BinaryTournament(P'_{t+1},N)
    $P'_{t+1} \leftarrow$ *Crossover&Mutation(Selected)*
    $P'_{t+1} \leftarrow$ *UpdatePopulation*(P'_{t+1})
End

Fig. 2. Pseudo Code of the SPEA2 Algorithm

Initialization: An initial population P_o consisting of N individuals is generated. The individuals are generated based on a chosen encoding scheme and physical constraints. Then, P'_0 set of N' size is produced. P'_0 consists of nondominated solutinons. If the number of nondominant solutions is less than N', it consists of some dominant solutions. A dominant solution is a solution that is superior to other solutions in the population at least one objective.

Fitness Assignment: In this stage, each individual is evaluated by the objective function and a fitness value is assigned. The density information is also considered when the fitness value is assigned. As a starting point, a strong value is assigned to each individual (Equation 1).

$$S(i) = |\{ j \mid j \in Pt + Pt \land i \succ j \}| \qquad (1)$$

In Equation 1, |.| indicates the severity of the set, and y corresponds to the Pareto dominance relation. The raw fitness value is calculated according to the strength value of each individual. This value is figured out by using the strengths of the dominant solutions in both the archive and population set. A density estimation technique is used when individuals have the same raw fitness values. The specific estimation technique is a simple inverse distance of the *k*-th nearest neighbour. In this technique, the distances of each individual in the population to each individual in the archive set is calculated. These distances are calculated in objective space and the results are stored in a list sorted increasingly. The *k*-th element gives the distance sought and it is represented by σ_i^k where *k* is equal to the square root of the sum of the population size and the archive size. Then the density is calculated using Equation 2.

$$D(i) = 1 / \sigma i^k + 2 \qquad (2)$$

Finally, the individual fitness value is calculated by adding density metric *D(i)* to the raw fitness value *R(i)* (Equation 3).

$$F(i) = R(i) + D(i) \qquad (3)$$

Environmental Selection: In this stage, all nondominated individuals in P_t (where t is the generation counter) are copied to P'_{t+1}. If the size of the P'_{t+1} exceeds the maximum population size *N*, the size of the population P'_{t+1} is reduced. If P'_{t+1} is less than *N*, the P'_{t+1} population is filled the dominant solutions in the P_t population and archive set .

Mating Selection: In this stage, the mating selection is performed. To fill the mating pool, individuals are selected from the P'_{t+1} through the binary tournament selection method.

Update: Crossover and mutation methods are applied to selected individuals and the P'_{t+1} population is updated. If the termination condition is not provided, the flow continues with the *Fitness Assignment* stage[14].

3. Robot Gripper Design Optimization

In this study, the problem is tackled according to the robot gripper model proposed by Osyczka et al. [15] (Fig.3). The model aims to optimize two objectives.

$$f_1(\mathrm{x}) = |max_z F_k(\mathrm{x},\mathrm{z}) - min_z F_k(\mathrm{x},\mathrm{z})| \qquad (4)$$

$$f_2(\mathrm{x}) = \frac{P}{minzFk(x,z)} \qquad (5)$$

f_1 is to minimize the difference between the minimum and maximum powers applied by the gripper for a specified distance. f_2 is to minimize the rate of the powers applied by gripper actuator and gripper ends.

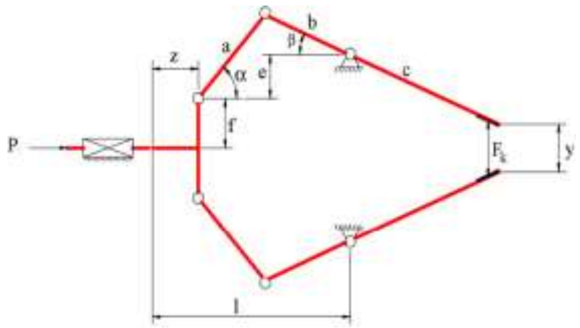

Fig. 3. The Scheme of Robot Gripper Mechanism[11]

There are seven design variables for the model. These variables and their ranges are defined in Eq. 6-12.

$$10.0 \leq a \leq 250.0 \tag{6}$$

$$10.0 \leq b \leq 250.0 \tag{7}$$

$$100.0 \leq c \leq 300.0 \tag{8}$$

$$0.0 \leq e \leq 50.0 \tag{9}$$

$$10.0 \leq f \leq 250.0 \tag{10}$$

$$100.0 \leq l \leq 300.0 \tag{11}$$

$$1.0 \leq \delta \leq \pi \tag{12}$$

Fig. 3 shows a robot gripper mechanism. The a, b, c, e, f and l are design variables of the robot gripper and represent the link lengths of the gripper in millimetres(mm). δ is the angle between b and c components in radian (rad).
The additional equations defined in eq. (13-18):

$$g^2 = (l - z)^2 + e^2 \tag{13}$$

$$\alpha = arccos\left(\frac{a^2+g^2-b^2}{2ag}\right) + \theta \tag{15}$$

$$\beta = arccos\left(\frac{b^2+g^2-a^2}{2bg}\right) - \theta \tag{15}$$

$$\theta = arctan\left(\frac{e}{l-z}\right) \tag{16}$$

$$F_k = \frac{Pb\,sin(\alpha+\beta)}{2c\,cos(\alpha)} \tag{17}$$

$$y(x,z) = 2[e + f + c\sin(\beta + \delta)] \tag{18}$$

Fig. 4. shows the geometric connections of the gripper. g in the eq. 13 symbolizes the distance between A and C points. α and β in eq. 14-15 denote the angle of the connections with horizontal reference lines.
θ in eq.16 indicates the angle between AC and AD (Fig 4). F_k stands for the power applied to the object grasped by the gripper. *y(x,z)* in eq.18 represents displacement of the gripper ends.
Seven constraints are defined in the model. Eq 19-25 describe the constraints.

$$g_1(x): Y_{min} - y(x, Z_{max}) \geq 0 \tag{19}$$
$$g_2(x): y(x, Z_{max}) \geq 0 \tag{20}$$
$$g_3(x): y(x,0) - Y_{max} \geq 0 \tag{21}$$
$$g_4(x): Y_g - y(x,0) - \geq 0 \tag{22}$$
$$g_5(x): (a+b)^2 - l^2 - e^2 \geq 0 \tag{23}$$
$$g_6(x): (l - Z_{max})^2 + (a-e)^2 - b^2 \geq 0 \tag{24}$$
$$g_7(x): l - Z_{max} \geq 0 \tag{25}$$

There are five geometric parameters in the model. Y_{min} is the minimal dimension of the gripping object; Y_{max} is the maximal dimension of the gripping object; Y_g is the maximal range of the gripper ends displacement; Z_{max} is the maximal displacement of the gripper actuator and P is actuating force of the gripper. The values are: Y_{min}=50mm; Y_{max}= 100mm; Y_g=150mm; Z_{max}=50mm; P=100N.
SPEA2 was adapted according to the objective functions, the range of the design variables and constraints to the problem. The penalty point is defined as 1000.0 for the solutions which do not provide the constaints. The adapted version of SPEA2 is depicted in Fig.5.

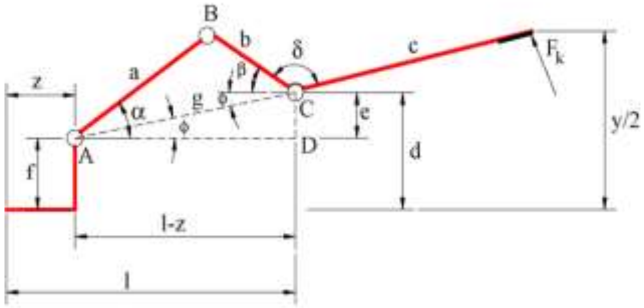

Fig. 4. Geometrical dependencies of the gripper mechanism. [11]

Input:*Population_size, Archive_size,P_crossover, P_mutation*
Output:*Archive*
Population ←InitializationPopulation(Population_size)
Archive←{}
While*(StopCondition())*
Calculate the constraints of the handled case of the problem
if *(all constraints are satisfied)*
FitnessPopulation←FitnessAssignment(Population)
FitnessArchive←FitnessAssigment(Archive)

Archive←ExtractNonDominatedSolution(Population,Archive)
if*(size(Archive)>Archive_size)*
FunctionReductionSize
ElseIf

FunctionFillOutWithDominatedSolution(Population,Archive)
End
Selected←BinaryTournament(Archive,Population_size)
Population←Crossover
Mutation(Selected,P_crossover,P_mutation
Population←Update(Population)
Else
Assign penalty value to the current solution as fitness value
End
End
End

Fig. 5. The adaptation of SPEA2 to the problem.

3.1. Experimental Studies

The experimental studies were carried out on MS Windows 10 x64 running on a PC with Intel(R) Core™ i7-3630QM 2.40 GHz CPU and 8 GB RAM. It is benefited from MOEA Framework (http://moeaframework.org) based on Java programming language

SPEA2 was applied to the problem with various inertial parameter for better results. Population size and maximum iterations are defined as 200 and 5000 respectively. Also, the crossover method is single point; the rate of crossover is 0.9; distribution index is 180.0; the mutation method is polynomial mutation; mutation rate is 0.1; the distribution index is 20.0.

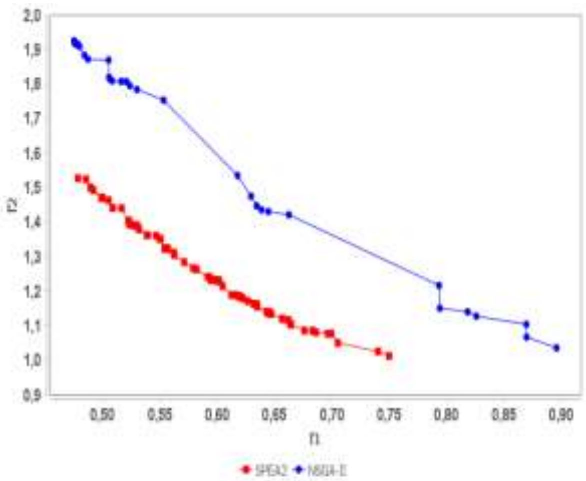

Fig. 6. The pareto optimal solutions obtained by SPEA2 and NSGA-II.

The solutions obtained by using NSGA-II in [12] are not detailed clearly for comparison. So, NSGA-II was also applied to the problem with the same parameters in [12]. Two Pareto optimal curves of the SPEA2 and NSGA-II for 5000 iterations are presented in Fig. 6. As a result of the optimization studies, 84 solutions were obtained by SPEA2 algorithm and 32 solutions were obtained by NSGA-II algorithm. In comparison with the same generation number, it was observed that better results were obtained with the SPEA2 algorithm. The results obtained with SPEA2 algorithm are f_1 is between 0.50-0.75 and f_2 is between 1-1.6. These value ranges are broader in the results obtained with the NSGA-II algorithm. With NSGA-II algorithm, f_1 is between 0.50-0.90 and f_2 is between 1-1.9. Some of the solutions are presented in Table 1.

The obtained results were compared with the results of the studies of Saravanan et al. [11], Datta and Deb[12], Osyczka[3] (Table 2). SPEA2 yields better solutions in terms of the values of the objective functions according to the comparison. Both of the objective values are less than the solutions of the other studies.

The results of the study were also analyzed in respect of the hypervolume, inverted generational distance (IGD) metrics and simulation time (Table 3). The IGD and the hypervolume indicators are used as quality metrics. Hypervolume is the dimensional field containing a set of solutions, that is, the n-dimensional volume of the cluster relative to some reference points. When it is adapted to multi-objective optimization, the solutions can be considered as the point of the n dimensional objective functions. That is, the hypervolume value of a cluster is the total size of the areas where the solutions are dominant[15]. The IGD measure is calculated on objective space, which can be viewed as an approximate distance from the Pareto front to the solution set in the objective space[16].

Table 1 Some Optimal Solutions Obtained by the SPEA2 Algorithm

Solution No	$f_1(x)$	$f_2(x)$	a	b	c	e	f	l	δ
1	0.593	1.240	231.800	208.509	242.530	21.779	10.045	150.588	1.835
2	0.656	1.119	231.800	208.506	218.852	21.779	10.795	150.590	1.833
3	0.696	1.076	231.798	208.519	210.322	21.747	11.087	151.199	1.833
4	0.498	1.470	231.798	208.506	287.470	21.778	10.155	150.549	1.837
5	0.663	1.103	231.800	208.507	215.818	21.779	10.757	150.529	1.837
6	0.749	1.011	231.799	208.370	196.922	21.775	11.069	152.736	1.836

Table 2 Result comparison between literature results [16] and proposed SPEA2

Design Variables	***GA[3]***	***NSGAII[11]***	***NSGAII[12] (large comp.)***	***NSGAII[12] (small comp.)***	***SPEA2***
a	135.0	88.1	250.0	250.0	231.78
b	90.53	52.98	250.0	233.0	208.37
c	102.2	100.0	243.6	210.3	204.43
e	0.0	29.95	0.0	14.0	21.77
f	1.28	69.89	37.0	15.0	11.08
l	170.57	126.96	100.0	180.0	152.72
δ	1.8	3.14	1.72	1.85	1.83
Population Size	400	100	200	200	200
Crossover Rate	0.6	0.9	0.9	0.9	0.9
Mutation Rate	0.08	1.0	0.1	0.1	0.1
Generation Number	400	150	N/A	1000	5000
$f_1(x)$	3.05	3.7168	1.55	0.734	0.704
$f_2(x)$	2.0	1.5767	0.994	0.998	1.049

According to hypervolume and inverted generational distance metrics, the algorithm was run 30 times with 5000 iterations to evaluate the performance of the algorithm. The difference is 0.802 between the arithmetic mean and standard deviation of the obtained solutions according to the hypervolume metric based on the volume of the dominant solutions in the objective space. Additionally, the difference between the arithmetic mean and the standard deviation is 0.0168 according to the IGD metric based on the convergence and diversity of the solutions obtained. The closer distance between standard deviation and the mean in the IGD indicates the high performance to achieve optimal design values.
In order to evaluate the runtime of the algorithm, the algorithm was run a total of 30 times with 5000 iterations. Accordingly, the shortest computition time of the algorithm is 2.279 s. The standart deviation of computation time is 0.4511.

Table 3 Statistical Results of SPEA2 Algorithm

	Hypervolume	***IGD***	***Simulation Time(s)***
Min	0.2893	0.0894	2.279
Max	0.8894	0.4073	4.472
Median	0.7222	0.1367	3.1705
Mean	0.6969	0.1533	3.243
Standart Deviation	0.1285	0.0661	0.4511

4. Conclusion

In this study, multi-objective optimization of the robot gripper ends was conducted by SPEA2 algorithm. The objectives of the study are to minimize both the power transfer ratio between the actuator and the ends of a gripper and the fluctuation of the power applied to an object by a gripper. The results were compared to the results of the different methods applied to the problem in the previous studies. When the optimization results are evaluated, the SPEA2 algorithm provides an obvious advantage to its competitors.
SPEA2 algorithm was applied for the first time to solve the presented robot gripper design problem. Therefore, SPEA2 might be considered as a good solution method to solve optimization problems related to robot design in the future. It is planned to develop a hybrid optimization approach for similar robot gripper design problems in the future.

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