Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 41 (2012) 426 – 435

Engineering Procedia

www.elsevier.com/locate/procedia

International Symposium on Robotics and Intelligent Sensors 2012 (IRIS 2012)

An Adaptive Particle Swarm Optimization Method for Solving the Grasp Planning Problem

Chiraz Walha*, Hala Bezine, Adel M. Alimi

REGIM: REsearch Group on Intelligent Machines, University of Sfax, National Engineering School of Sfax (ENIS), BP 1173, Sfax, 3038, Tunisia

Abstract

This paper proposes an adaptive particle swarm optimization (APSO) approach to solve the grasp planning problem. Each particle represents a configuration set describing the posture of the robotic hand. The aim of this algorithm is to search for the optimum configuration that satisfies a good stability. The approach uses a Guided Random Generation (GRG) to guide the particles in the generating process. A shape-based object "parameter factor" is generated from the GRG process so that, it can be considered in the fitness function. According to the number of contacts between the fingertips and the object, the algorithm can take off the inactive particles. The kinematic of the modeled hand is described and incorporated in the fitness function in order to compute the contact positions. The APSO is tested in the HandGrasp simulator with four different objects and the experimental results demonstrate that this approach outperforms the compared simple PSO in terms of solution accuracy, convergence speed and algorithm reliability.

Keywords: Grasp Planning Problem; Adaptive PSO; Robotic Hand.

Nomenclature

θ_{ij}	articulation angle of the finger i, (from little finger to thumb), joint j (from distal to proximal)
l_{ij}	phalange length of the finger i, (from little finger to thumb), joint j (from distal to proximal) (cm)
${}_i{}^jT_k$	transformation matrix from the coordinator j to k of the finger i (from little finger to thumb)
C_{ij}	cosinus (θ_{ij})
S_{ij}	sinus (θ_{ij})
X_i	position and orientation of the joint i
q_i	configuration system of the joint i
J_i	Jacobian matrix of the joint i
Cg	configuration set of the hand
$\theta_x, \theta_y, \theta_z$	orientation of the wrist according respectively to the x, y and z axis

* Corresponding author. Tel.: +216-98-825-468; fax: +216-74-677-545.
E-mail address: chiraz.walha@ieee.org

1877-7058 © 2012 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.
doi:10.1016/j.proeng.2012.07.194

np	number of particles
p_k	particle k, $k = 1..np$
v_k	velocity associated to p_k, $k = 1..np$
p_k^{pbest}	personal best particle, $k = 1..np$
p^{gbest}	global best particle
nit	number of iterations
f_k	fitness value of p_k, $k = 1..np$
f_k^{pbest}	fitness value of personal best particle, $k = 1..np$
f^{gbest}	fitness value of global best particle
$ibest$	index of particle with best fitness value
c_1, c_2	acceleration constants
rand()	random function in the range [0, 1]
nc	number of fingers in contact with object
θ_{ki}	internal angle at vertex i of the contact polygon associated to the particle p_k, $k = 1..np$ (in degrees)
$\bar{\theta}_k$	average internal angle of the corresponding regular polygon associated to the particle p_k, $k = 1..np$ (in degrees)
$\theta_k^{\max}$	sum of the internal angles when the polygon has the poorest conditioned shape, associated to the particle p_k, $k = 1..np$ (in degrees)
$\overrightarrow{F_i}$	Force associated to the finger i, i=1,..,nc
m_i	mass of the finger i, i=1,..,nc
$\overrightarrow{vf_i}$	velocity associated to the finger i, i=1,..,nc

1. Introduction

One of the tasks of a service robot is to grasp an object and bring it to another place. This process involves many steps and difficulties like detecting the emplacement of the object, move to a suitable emplacement, localize its proper hand, reach the object and finally form the appropriate configuration of the hand to firmly grasp the object. Each of these steps involves the knowledge of the environment in case of possible obstacles, the shape and parameters of the object like weight and emplacement [1] and the joint structure of the robotic hand [2]. Thus, it creates a high dimensionality of the configuration space. Some researchers were interested in associating the grasp process with the task [3-4]. Most of them use the shape of the object to generate the form of the hand [5]. Others were interested in adding a learning process from a database of grasp examples [6] or from a human demonstration [7-10].

The rest of the paper is organized as follows. Section 2 specifies the addressed problem and presents a proper algebraic formulation to the problem. Section 3 describes the kinematic structure of the hand system. Section 4 explains the proposed method. Section 5 presents some experiments illustrating the method's performance and, finally, Section 6 summarizes the conclusions and points deserving further attention.

2. Grasp Planner

The main purpose of a grasp planner is to explore the dexterous manipulation space of the multi-fingered robot hand and to find the best configuration of the fingers that enables a stable grasp as swiftly as possible. For a successful gripping of the object, several grasp planners have been developed under two main approaches [11]: empirical and analytical. The empirical (knowledge-based) approach is motivated by the imitation of the human hand behavior like Li and Pollard [5] who presented a matching algorithm to select appropriate grasps from a database based on the shape of the object. The analytic approach is based on the study of the robotic hand from a mechanical point of view. We can find the works of Fuentes *et al.* who used a genetic approach [12] to tackle this problem, Borst *et al.* [13] who presented a heuristic approach to plan a precision grasp for a 3D objects and Pelossof, *et al.* [14] who presented an SVM approach under the simulator "Grasp it!"[15].

A classification of this planners has been described by [16] as a forward and backward directions. The forward direction starts from the wrist of the robotic hand to the object and follow these steps:

- Close the fingers on the object
- Compute the values of the joint angles using the kinematic model of the hand
- Detect the positions of the fingertips at collision, using the collision detection technique
- Evaluate the grasp quality of the grip

This methodology is evaluated under the simulator "Grasp it", which have been used for analyzing and visualizing the grasps of a variety of different hands and objects. This planner includes two phases, the first one is to generate a configuration of the hand using shape primitives [17], and the second one, is to evaluate the quality of these grasps [18].

The backward direction is object-centered solution and is presented as follow:

- Contact points are randomly or analytically located on the object surface
- Evaluate the grasp quality
- Find the corresponding feasible finger joint position using an inverse kinematic algorithm

In this paper, we are most interested in algorithms for the fast and autonomous generation of precision grasps where only the fingertips are in contact with the object. Furthermore, we assume that the position of the object is reachable by the hand and the position and orientation of the object is known.

3. Modeled Hand

3.1. Distribution of the degrees of freedom of the modeled hand

The modeled hand is a five-fingered human hand. Indeed, the human hand has 27 degrees of freedom (DOF) presented like this [19]:

- six DOF at the wrist : 3 rotations and 3 translations,
- four DOF for each finger : 1 DOF (flexion/extension) at each of the three joints and 1 DOF (abduction/adduction) at the metacarpophalangeal joint [20],
- unlike the other fingers, the thumb has five DOF [21]: 3 DOF at the carpo-metacarpal joint (abduction/adduction, flexion/extension and a pseudo-rotation) and 1 DOF for each of the two other joints.

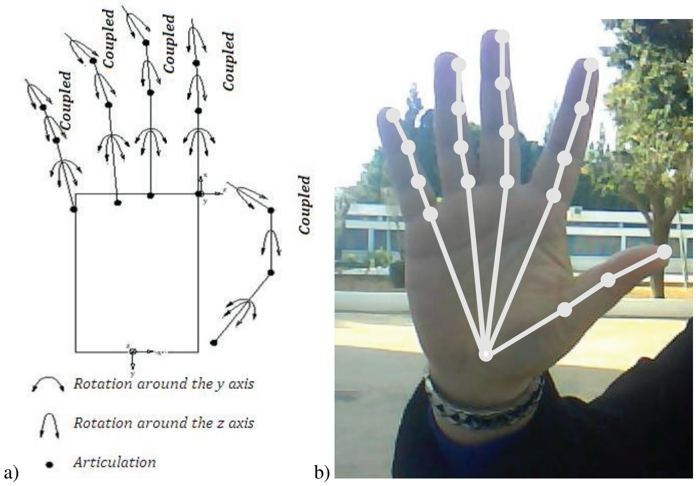


Fig. 1. a) Distribution of the 21 degrees of freedom of the modeled hand. b) Joints of the hand

The human hand interacts under static and dynamic constraints [22]. The static constraints explain the limits of joint angles and the dynamic constraints describe the interconnection between the degrees of freedom of the finger joints.

Amongst these biomechanical constraints, we are interested in the relationship between the distal and proximal phalanges and which can be translated by the following equation:

$$\theta_{i2} = \frac{3}{2}\theta_{i1}, i = 1...5 \tag{1}$$

For that reason and to model the hand, we opted for an optimization of the DOF by coupling the distal and proximal joints. This allows us to simplify the model to 21 DOF (Fig. 1.a): 3 DOF for each of the fingers and 6 DOF for the wrist.

3.2. Kinematic of the modeled hand

The kinematic of the modeled hand is used to determine the positions and velocity of articulations in space relative to the robot base coordinator (Fig. 1.b). The Denavit-Hartenberg parameters [23] are given in this table:

Table 1: The Denavit-Hartenberg parameters of the finger with 3 DOF

Articulation	θ_{ij}	d_{ij}	a_{ij}	α_{ij}	Variable of the articulation
1	θ_{i1}	*0*	l_{i1}	*0*	θ_{i1}
2	$\frac{3}{2}\theta_{i1}$	*0*	l_{i2}	*0*	θ_{i1}
3	θ_{i2}	*0*	l_{i3}	θ_{i3}	θ_{i2}, θ_{i3}

Therefore, the transformation matrix from the coordinator 0 to 3 of the finger i is given by:

$$ {}^{0}_{i}T_{1} = \begin{bmatrix} C_{i1} & -S_{i1} & 0 & l_{i1}C_{i1} \\ S_{i1} & C_{i1} & 0 & l_{i1}S_{i1} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$$ {}^{1}_{i}T_{2} = \begin{bmatrix} \cos\left(\frac{3}{2}\theta_{i1}\right) & -S_{i1} & 0 & l_{i2}\cos\left(\frac{3}{2}\theta_{i1}\right) \\ \sin\left(\frac{3}{2}\theta_{i1}\right) & \cos\left(\frac{3}{2}\theta_{i1}\right) & 0 & l_{i2}\sin\left(\frac{3}{2}\theta_{i1}\right) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$ {}^{2}_{i}T_{3} = \begin{bmatrix} C_{i2} & -S_{i2}C_{i3} & S_{i2}S_{i3} & l_{i3}C_{i2} \\ S_{i2} & C_{i2}C_{i3} & -C_{i2}S_{i3} & l_{i3}S_{i2} \\ 0 & S_{i3} & C_{i3} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$ {}^{0}_{i}T_{3} = {}^{0}_{i}T_{1} \times {}^{1}_{i}T_{2} \times {}^{2}_{i}T_{3} \tag{5}$$

The forward kinematic model is as follow:

$$\delta X_i = J_i \, \delta q_i \tag{6}$$

4. Adaptive Particle Swarm Optimization Approach (APSO)

Particle swarm optimization (PSO) is a meta-heuristic optimization technique in artificial intelligence inspired by the behavior of flocks of birds [24]. Each particle is defined by its location, speed and previous best particle in the search. The particles are influenced by each other. The algorithm calculates the movement of flocks in discrete time steps and constantly adjusts the values describing the particle. Although PSO is a relatively new technique, but, it gained popularity in solving various optimization problems. Its main advantages are the easy implementation and the fast convergence to the optimum for a wide range of purpose functions. This technique has received more and more attention because of its simplicity and success. Inspired by this, we propose an adaptive particle swarm optimization (APSO) based algorithm for grasp planning problem in which each of the configuration set of the hand is a particle (Fig. 2).

4.1. Configuration set

The output of the grasp planner is the final posture of the hand. This configuration represents the 21 degrees of freedom of the modeled hand. Yet, the position of the wrist is computed apart. It can be controlled by a human operator or computed separately after evaluating the wrench space around the object. Thus, the configuration Cg contains the values of joint's angles for each of the fingers and the orientation of the wrist. It's represented as follow:

$$Cg = \begin{pmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \\ \theta_{31} & \theta_{32} & \theta_{33} \\ \theta_{41} & \theta_{42} & \theta_{43} \\ \theta_{51} & \theta_{52} & \theta_{53} \\ \theta_x & \theta_y & \theta_z \end{pmatrix} \tag{7}$$

4.2. Guided Random Generation (GRG)

The first step of the APSO approach is the generation of possible solutions p_k. In a simple PSO algorithm, the generation is random. However, in the APSO, a Guided Random Generation process is computed. The central idea of this system is the anthropomorphic studies of the human hand [25-26]. Therefore, we generate randomly the joint angles that have to satisfy the limitations of Table 2 and with 2 minimum contacts with the object. Then, we generate a "parameter factor" based on the shape of the object, which classify the object into sub-classes. The final step of GRG, is the verification test, it detects the deformed positions of the fingers caused from an illegal collision with the object (case where a finger enter the object perimeter) or with another finger, in that case, we generate another values for the corresponding finger.

Table 2: The angle's limit of the joints

Finger	Distal (°)	Proximal (°)	Pivot (°)
Little finger	$-30 \le \theta_{11} \le 90$	$0 \le \theta_{12} \le 90$	$-10 \le \theta_{13} \le 40$
Ring	$-30 \le \theta_{21} \le 90$	$0 \le \theta_{22} \le 90$	$-10 \le \theta_{23} \le 20$
Middle	$-30 \le \theta_{31} \le 90$	$0 \le \theta_{32} \le 90$	$-15 \le \theta_{33} \le 15$
Index	$-30 \le \theta_{41} \le 90$	$0 \le \theta_{42} \le 90$	$-20 \le \theta_{43} \le 10$
Thumb	$-10 \le \theta_{51} \le 30$	$0 \le \theta_{52} \le 90$	$-10 \le \theta_{53} \le 100$

4.3. General process

Assuming p_k the particles represented by the configuration set of the hand, for each iteration, the velocity v_k and the particle p_k are updated. According to the fitness values of the updated individuals, the personal best angle p_k^{pbest} of each particle and the global best position p^{gbest} among all the particles are computed. In APSO the individuals move through the solution space with perturbations of their position which are influenced by other swarm members. Therefore, the APSO searches the global optimum solution by adjusting the trajectory of each particle towards its personal best position and the global best position.

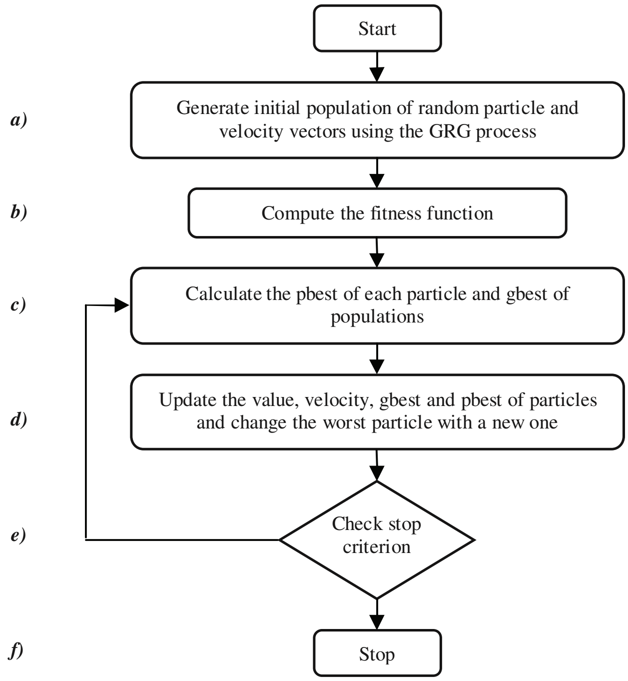


Fig. 2. Main process of the APSO algorithm.

During the process, if there has been not enough improvement in a neighborhood, the worst particle will be replaced with a new generated one. According to the above description, the process for implementing APSO (Fig. 2) is as follows:

a) Initialize APSO with *np* and *nit*,

- Generate the particle population using GRG process.
- Generate randomly initial velocity vectors v_k

b) Compute the fitness value of each particle and set initial p_k^{pbest} , f_k^{pbest} and initial p^{gbest} , f^{gbest} for the initial population.

- Set $f_k = fitness(p_k), k = 1, 2, \ldots, np$
- Set $p_k^{pbest} = p_k$ and $f_k^{pbest} = f_k, k = 1, 2, .., np$
- Find the index $ibest$ of the particle with best fitness value by $ibest = \arg(\max_{k=1}^{np} f_k^{pbest})$
- Set $p^{gbest} = p_{ibest}^{pbest}$ and $f^{gbest} = f_{ibest}^{pbest}$
- Set $iteration = 1$

c) Update p_k^{pbest}, p^{gbest} and f_k^{pbest}, f^{gbest}.

- Compute $f_k = fitness(p_k), k = 1, 2, \ldots, np$

- if $f_k > f_k^{pbest}$ then set $p_k^{pbest} = p_k$ and $f_k^{pbest} = f_k$
- if $f_k^{pbest} > f^{gbest}, k = 1, 2, \ldots, np$ then set $p^{gbest} = p_k^{pbest}$ and $f^{gbest} = f_k^{pbest}$

d) Update the velocity vector v_k and the vector p_k of each particle.

- Update $v_k = v_k + c_1 rand()\left(p_k^{pbest} - p_k \right) + c_2 rand()\left(p^{gbest} - p_k \right), k = 1, 2, \ldots, np$
- Set $p_k = p_k + v_k, k = 1, 2, \ldots, np$
- Set $v_k = v_k w,\ w \in [0,1],\ k = 1, 2, \ldots, np$
- The worst particle will be updated with a new generated one.

e) $iteration = iteration + 1$, if $iteration > nit$ then go to **f)** , else go to **c)**

f) The desired solution is the global best p^{gbest} with the best fitness value f^{gbest} .

4.4. Fitness function

The fitness function is based on a quality measure [27] associated with the position of the contact points. It takes into account the object properties as the shape, the weight, the size, the location and the "parameter factor" of the GRG process. From the configuration set p_k and with the kinematic of the hand, the positions of the fingertips are calculated as well as the number and positions of the contact points. Park and Starr [28] have proven that when the contact points are distributed in a uniform way over the object surface, it improves the grasp stability. Inspired by this, the fitness function is given by [29]:

$$fitness(p_k) = \frac{1}{\theta_k^{\max}} \sum_{i=1}^{nc} \left| \theta_{ki} - \bar{\theta}_k \right| \tag{8}$$

$$\bar{\theta}_k = 180 \frac{nc - 2}{nc} \tag{9}$$

$$\theta_k^{\max} = (nc - 2)(180 - \bar{\theta}_k) + 2\bar{\theta}_k \tag{10}$$

The force of the fingers is computed using the equation:

$$\overrightarrow{F_i} = m_i \overrightarrow{vf_i} \tag{11}$$

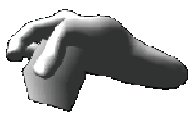
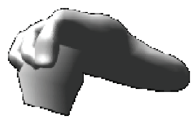
Each $\overrightarrow{F_i}$ is directed to the center of mass of the object. This insures a stable grasp and simplifies the computing of the force magnitudes which is equal to zero:

$$\sum_{i=1}^{nc} \overrightarrow{F_i} = \vec{0} \tag{12}$$

5. Experimental results

We tested this approach under HandGrasp [30] which can simulate the trajectories of the fingers in space (Fig. 3). HandGrasp is an environment used for hand grasping simulation and can be expanded since it's developed under a modular architecture [31]. This approach is experienced with four different objects: sphere, cube, barrel and fish. The global best particle at the iteration 5, 20 and 50 are shown in Table. 3. We compared the results with the same objects using a simple PSO algorithm [32-33].

Table 3: Comparison results between simple PSO and APSO

Object	Approach	Iteration=5	Iteration=20	Iteration=50
Sphere	Simple PSO			
	APSO			
Cube	Simple PSO			
	APSO			
Barrel	Simple PSO			
	APSO			
Fish	Simple PSO			
	APSO			

The parameters of the algorithms were:

- *np* = 60
- number of neighborhood = 5
- *ite* = 50
- Diameter of the sphere = 5 cm
- Length of the cube = 7 cm
- Length of the barrel = 11 cm, diameter = 3 cm
- Dimension of the fish : length = 29 cm, width= 6 cm, height = 7 cm

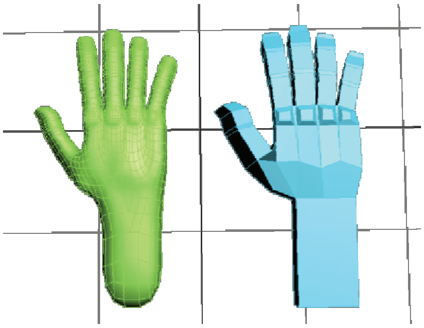


Fig. 3. Simulated hand.

We remark that the convergence to optimum solution in APSO is more guided and has a better solution (minimum two contact points with the object) than with simple PSO. Also, with the continued renewal and improvement of the population, the APSO approach outperformed the simple PSO on term of solution accuracy, convergence speed and algorithm reliability, although, it is clear that the simple PSO approach is faster than the APSO approach due to the CPU (Central Processing Unit) consuming of the GRG process.

6. Conclusion

In this paper, a grasp planner based on an adaptive particle swarm optimization APSO is proposed to search the wrench space of the graspable area. The output of this algorithm is the optimum configuration set of the hand. This grasp planner is set for the precise grasp when only the fingertips are in contact with object. The aim of this planner is to ensure the stability of the grip. In order to guaranty a good grasp, the quality of measure is computed under the fitness function. Furthermore, a GRG system was established to generate a guided random generation of configuration set. We tested this method under the HandGrasp simulator with four different objects. The results were compared with a simple PSO algorithm and it showed the effectiveness of the APSO compared with the simple PSO. The fitness function can be varied as required by the task.

In future works, we will adopt a multi-object particle swarm optimization (MOPSO) [34] approach to build a list of leaders which can be saved as a "good" grasps in a database.

Acknowledgements

The authors would like to acknowledge the financial support of this work by grants from General Direction of Scientific Research (DGRST), Tunisia, under the ARUB program.

References

[1] Morales A., Asfour T., and Azad P., 2006. "Integrated grasp planning and visual object localization for a humanoid robot with five-fingered hands," IEEE/RSJ Int. Conf. on Intelligent Robots and Systems.
[2] Boughdiri, R.; Bezine, H.; M'Sirdi, N. K.; Naamane, A. and Alimi, A. M., 2011. "Dynamic modeling of a multi-fingered robot hand in free motion," International Multi-Conference on Systems, Signals & Devices SSD'11, Sousse Tunisia.
[3] Pollard N. S. and Wolf A., 2004. "Grasp synthesis from example: tuning the example to a task or object," Workshop on Multi-point Interaction in Robotics and Virtual Reality, IEEE International Conference on Robotics and Automation, pp 77-90.
[4] Chang L. Y., Srinivasa S. S., and Pollard N. S., 2010. "Planning pre-grasp manipulation for transport tasks," Proceedings of the IEEE International Conference on Robotics and Automation, pp 2697-2704, Anchorage, Alaska.

[5] Li, Y. and Pollard, N. S., 2005. "A shape matching algorithm for synthesizing humanlike enveloping grasps," IEEE-RAS International Conference on Humanoid Robots, Tsukuba, Japan, pp 442-449.
[6] Pollard N. S., 2004. "Closure and Quality Equivalence for Efficient Synthesis of Grasps from Examples", International Journal of Robotics Research 23(6), 595--614.
[7] Dang H. and Allen P. K., 2010. "Robot Learning of Everyday Object Manipulations via Human Demonstration," IEEE/RSJ International Conference on Intelligent Robots and Systems October 18-22, 2010, Taipei, Taiwan.
[8] Ehrenmann M., Rogalla O., Zoellner R., and Dillmann R., 2001. "Teaching service robots complex tasks: Programming by demonstration for workshop and household environments," In Proceedings of the IEEE International Conference on Field and Service Robotics (FRS).
[9] Aleotti, J.and Caselli, S., 2008. "Grasp Programming by Demonstration: A task-based quality measure," The 17th IEEE International Symposium on Robot and Human Interactive Communication RO-MAN 2008, vol., no., pp.383-388, 1-3.
[10] Ekvall S. and Kragic D., 2005. "Grasp recognition for programming by demonstration," In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA), pages 748-753.
[11] Mishra B. and Silver N., 1989. "Some discussion of static gripping and its stability," IEEE Trans. on Systems, Man, and Cybernetics 19(4), 783–796 .
[12] Fuentes, O.; Marengoni, H. F. and Nelson, R. C., 1994. "Vision-based planning and execution of precision grasps," TR546, Computer Science Dept., U.Rochester.
[13] Borst, C.; Fischer, M. and Hirzinger, G., 1999. "A fast and robust grasp planner for arbitrary 3D objects," In ICRA'1999, Proc. IEEE Intl. Conf. on Robotics and Automation, pages 1890 - 1896, Detroit, Michigan, USA.
[14] Pelossof, R., Miller, A. T., Allen, P. K. and Jebara, T., 2004. "An SVM learning approach to robotic grasping," IEEE Int. Conf. on Robotics and Automation, New Orleans, pp. 3512-3518.
[15] Miller, A. T. and Allen, P. K., 2004. "Graspit!: a versatile simulator for robotic grasping," IEEE Robotics and Automation Magazine, vol. 11, no. 4, pp. 110-122.
[16] Zhixing X., Stadie U., Zoellner J. M., and Dillmann R., 2009. "An efficient grasp planning system using impulse-based dynamic simulation," Multybody Dynamics, Warsaw, Poland.
[17] Miller, A. T., Knoop, S., Christensen, H. I. and Allen, P. K., 2003. "Automatic grasp planning using shape primitives," In Proceedings of the IEEE International Conference on Robotics and Automation, pp. 1824-1829.
[18] Miller A. T. and Allen, P. K., 1999. "Examples of 3D grasp quality computations," In Proceedings IEEE International Conference on Robotics and Automation, Detroit, MI, pp. 1240-1246.
[19] Elkoura, G. and Singh, K., 2003. "Handrix - animating the human hand," Proceedings of the 2003 ACM SIGGRAPH/Eurographics Symposium on Computer Animation pp. 110-119.
[20] Agur, A. M. R. and Lee, M. J., 1999. "Grant's Atlas of Anatomy," Lippincott Williams and Wilkins, 10th Edition.
[21] Buchholz, B. and Armstong, T. J., 1992. "A kinematic model of the human hand to evaluate its prehensile capabilities," J. Biomecanics, 25 : 2, pp. 149-162.
[22] Wagner C., 1988 . "The pianist's hand: anthropometry and biomechanics," Ergonomics 31: 1, pp. 97-131.
[23] Denavit, J. and Hartenberg, R.S., 1955. "A kinematic notation for lower-pair mechanisms based on matrices," *Trans ASME J. Appl. Mech,* 23:215–221.
[24] Kennedy, J. and Eberhart, R. C., 1995. "Particle swarm optimization," Proceedings of IEEE International Conference on Neural Networks, Piscataway, pp. 1942-1948.
[25] Brand, P. W. and Hollister, A. M., 1999. "Clinical Mechanics of the Hand," Mosby, Inc. Third edition.
[26] Buchholz, B.; Armstrong, T. and Goldstein, S., 1992. "Anthropometric data for describing the kinematics of the human hand," Ergonomics, 35(3):261–273.
[27] Bicchi, A., 2000. "Hands for dexterous manipulation and robust grasping: A difficult road towards simplicity," IEEE Trans. Robotics and Automation 16(6), 652–662.
[28] Park Y.C. and Starr G.P., 1992. "Grasp synthesis of polygonal objects using a three-fingered robotic hand". Int. J. Robotics Research 11(3), 163–184.
[29] Kim B., Oh S., Yi B. and Suh I.H. (2001). Optimal grasping based on non-dimensionalized performance indices. Proc. IEEE IROS 2001, pp. 949–956.
[30] Walha, C.; Bezine, H.; M'sirdi, N. K.; Naamane, A. and Alimi, A. M., 2010. "Contribution to the development of a theory of generation of grasping movements". WIMTA'2010, The 17th Workshop Intelligent Machines: Theory and Applications, Mahdia, Tunisia.
[31] Walha, C., Bezine, H., M'sirdi, N. K., Naamane, A. and Alimi, A. M., 2011. "HandGrasp: a new simulator for human grasping". Workshop on Autonomous Grasping at ICRA'2011, IEEE International Conference on Robotics and Automation, Shanghai Chine.
[32] Walha, C., Bezine H., and Alimi, A. M., 2012. "Towards a Particle Swarm Optimization Approach for Grasp Planning Problem," IEEE International Conference on Biomedical Robotics and Biomechatronics, June 24-27, 2012 Roma, Italy.
[33] Walha, C., Bezine H., and Alimi, A. M., 2012. "A Particle Swarm Optimization Algorithm for the Grasp Planning Problem," 9th International Conference on Informatics in Control, Automation and Robotics, July 28-31, 2012 Roma, Italy.
[34] Coello C. A., and Reyes-Sierra M.. 2006. "Multi-Objective Particle Swarm Optimizers: A Survey of the State-of-the-Art," International Journal of Computational Intelligence Research 2.3: 287-308.