

A Particle Swarm Optimization Algorithm for the Grasp Planning Problem

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Abstract: Computing a set of contact points between a robotic hand and an object in order to fulfill some criteria is the main problem of the grasp planning. An automatic grasp planning can produce a set of joint angles defining a configuration of the robotic hand. The huge number of solutions that satisfy a good grasp is the main difficulty of such a planner. In this paper, we represent the grasp planning problem as an optimization problem and we propose a new algorithm based on a Particle Swarm Optimization (PSO) technique. To generate the positions of the fingertips, the kinematic of the hand is modeled. Therefore, a simple PSO algorithm is described to optimize the workspace of the operating hand based on a quality of measure of the grasp. The simulation results support the effectiveness of our approach.

1 INTRODUCTION

The most complicated task that a robot is asked to achieve is to take an object and bring it to another place. Many configurations of the hand can be found considering the high dimension of the wrench space, the huge number of possible contact points in the surface of the object and the many degrees of freedom of the robotic hand. However, finding the positions of the fingertips on the object can be really competitive since some criteria had to be taken into account like the stability of the grip, minimization of the friction, etc. Therefore, grasp planning problem is considered as an optimization problem.

To grasp an object, some information is needed, like the position and the shape of the object (Infantino et al., 2003), its material, the actual localization of the robotic hand (Chesi and Hung, 2007) (Chesi, 2009) and its kinematic model (Boughdiri et al., 2011), etc. All this information should be considered during the grasping process. Some can be collected using camera devise or sensor, and others, like the material and the weight of the object, should be defined by the user. This information serves as input to the grasp planner. The output is the position of the fingertips on the object or the configuration of the posture of the hand (the joints angles of the fingers and wrist associated with the position of the hand).

In this paper, we propose a novel grasp planner based on Particle Swarm Optimization algorithm. The main purpose of the method is to explore the dexterous manipulation space of a multi-fingered robot hand and to find the best configuration of the fingers that enables the grasp as fast as possible.

For a successful gripping of the object, several grasp planners have been developed (Shimoga, 1996), (Coelho and Grupen, 1996), (Morales et al., 2006). Zhixing et al., (2009) have classified these planners on forward and backward direction. The forward direction follows these steps:

- close the fingers on the object
- extract 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

This methodology is evaluated in the simulator "Grasp it" (Miller and Allen, 1999), (Miller and Allen, 2004), which have been used for analyzing and visualizing the grasps of a variety of different hands and objects. This grasp planner includes two phases, the first one is to generate a configuration of the hand using shape primitives (Miller et al., 2003), and the second one, is to evaluate the quality of these grasps. The backward direction is object-centred 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

Fuentes, Marengoni and Nelson (1994) have presented a grasp planner based on genetic algorithm. They posed the grasp planning problem as a search problem. Borst et al., (1999) used a heuristic approach to plan a precision grasp for a 3D objects. Pelossof et al., (2004) presented an SVM approach involving a combination of numerical methods to recover parts of the grasp quality surface with any robotic hand in the simulator “Grasp it!”. Li and Pollard (2005) presented a matching algorithm to select appropriate grasps from a database based on the shape of the object.

2 MODEL OF THE HAND

2.1 Presentation of the Degrees of Freedom of the Modeled Hand

Our hand is a five-fingered human hand. Eventually, the human hand has 27 degrees of freedom (Elkoura and Singh, 2003) deployed like this:

- 6 at the wrist : 3 rotations and 3 translations,
- 4 for each finger : 1 DOF for flexion/extension at each of the three joints and 1 DOF for the abduction/adduction (Agur and Lee, 1999)
- the thumb has 5 DOF (Buchholz and Armstrong, 1992), the carpo-metacarpal joint has 3 degrees of freedom: abduction / adduction, flexion / extension and a pseudo-rotation due to incongruity between the carpal bones and the base of the thumb metacarpal and the relaxation of the ligaments connecting them and 1 for each of the two joints.

The human hand interacts under static and dynamic constraints (Wagner, 1988). 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:

$$\text{Angle}_{\text{PIP joint}} = \frac{3}{2} \text{Angle}_{\text{DIP joint}} \quad (1)$$

Therefore 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 (Figure 1): 3 DOF for each of the fingers and 6 DOF for the wrist.

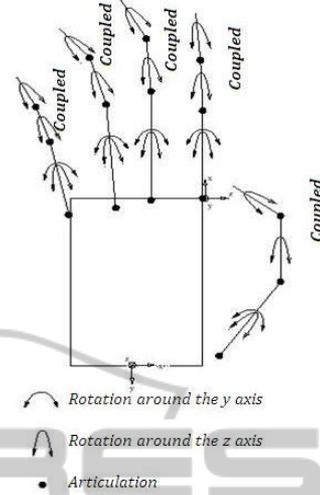


Figure 1: Distribution of the 21 degrees of freedom of the modeled hand.

2.2 Kinematics of the 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. The Denavit-Hartenberg parameters (Denavit and Hartenberg, 1955) 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	$3/2 * \theta_{i1}$	0	l_{i2}	0	θ_{i1}
3	θ_{i2}	0	l_{i3}	θ_{i3}	θ_{i2}, θ_{i3}

Where θ_{i1} , θ_{i2} and θ_{i3} represent the angles of the articulations of the finger i and l_{i1} , l_{i2} and l_{i3} represent the length of each phalange of the finger i . Therefore, the transformation matrix from the coordinator 0 to 3 of the finger i is given by:

$${}^0T_1 = \begin{bmatrix} C_{i1} & -S_{i1} & 0 & l_{i1}C_{i1} \\ S_{i1} & C_{i1} & 0 & l_{i1}S_{i1} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (2)$$

$${}^1T_2 = \begin{bmatrix} \cos\left(\frac{3}{2}\theta_{i1}\right) & -S_{i1} & 0 & l_{i2}\cos\left(\frac{3}{2}\theta_{i1}\right) \\ \sin\left(\frac{3}{2}\theta_{i1}\right) & \cos\left(\frac{3}{2}\theta_{i1}\right) & 0 & l_{i2}\sin\left(\frac{3}{2}\theta_{i1}\right) \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$${}^2T_3 = \begin{bmatrix} C_{i2} & -S_{i2}C_{i3} & S_{i2}S_{i3} & l_{i3}C_{i2} \\ S_{i2} & C_{i2}C_{i3} & -C_{i2}S_{i3} & l_{i3}S_{i2} \\ 0 & S_{i3} & C_{i3} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

$${}^0T_3 = {}^0T_1 \times {}^1T_2 \times {}^2T_3 \quad (5)$$

We assume that,

i represents the finger, $i = 1..5$

$C_{ij} = \cos \theta_{ij}, i = 1..5, j = 1..3$

$S_{ij} = \sin \theta_{ij}, i = 1..5, j = 1..3$

The forward kinematic model is as follow:

$$\delta X = J \delta q \quad (6)$$

Where X represents the position and orientation of the joint, q is the configuration system and J is the Jacobian matrix.

3 PSO ALGORITHM

PSO (particle swarm optimization) (Kennedy and Eberhart, 1995) is a population based on a search algorithm and is initialized with a population of random solutions, called particles. Not like other computational techniques, each particle in PSO is also associated with a velocity. The particles fly into space with velocities which are dynamically adjusted based on their historical behavior. This technique has received more and more attention because of its simplicity and success.

Inspired by this, we propose a particle swarm optimization based algorithm for grasp planning problem in which each of the joints of the hand is viewed as a particle and we integrated this algorithm in our grasp planner.

Table 2: The angle's limit of the joints.

Finger	Distal	Intermediate	Proximal	Pivot
Thumb	$-10 \leq \alpha \leq 30$	$0 \leq \alpha \leq 60$	$0 \leq \alpha \leq 90$	$-10 \leq \alpha \leq 100$
Index	$-30 \leq \alpha \leq 90$	$0 \leq \alpha \leq 110$	$0 \leq \alpha \leq 90$	$-20 \leq \alpha \leq 10$
Middle	$-30 \leq \alpha \leq 90$	$0 \leq \alpha \leq 110$	$0 \leq \alpha \leq 90$	$-15 \leq \alpha \leq 15$
Ring	$-30 \leq \alpha \leq 90$	$0 \leq \alpha \leq 110$	$0 \leq \alpha \leq 90$	$-10 \leq \alpha \leq 20$
Little finger	$-30 \leq \alpha \leq 90$	$0 \leq \alpha \leq 110$	$0 \leq \alpha \leq 90$	$-10 \leq \alpha \leq 40$

The final purpose of the grasp planner is to find the best location of contact points in the surface of

the object satisfying some criteria. Assuming $p_k, k = 1, 2, \dots, m$ the particles represented by a configuration of the hand. It contains the values of joint's angles for each of the fingers which satisfy the limitations of Table 2 (Brand and Hollister, 1999), (Buchholz et al., 1992). The velocity associated to p_k is $v_k, k = 1, 2, \dots, m$ with m the number of particles.

For each iteration, the velocity $v_k, k \in \{1, 2, \dots, m\}$ and the particle $p_k, k \in \{1, 2, \dots, m\}$ are updated. According to the fitness values of the updated individuals, the personal best angle $p_k^{pbest}, k \in \{1, 2, \dots, m\}$ of each particle and the global best position $p_k^{gbest}, k \in \{1, 2, \dots, m\}$ among all the particles are updated. For the update of the velocities in PSO, a particle p_k is influenced by its personal best position p_k^{pbest} and the global best position p^{gbest} . Hence, the PSO searches the global optimum solution by adjusting the trajectory of each particle toward its personal best position and the global best position. According to the above description about the PSO, the procedure of the PSO is described as following:

Step 1. Initialize the PSO with

- m , the number of particles
- G , the number of iterations
- Generate randomly initial configurations $p_k, k \in \{1, 2, \dots, m\}$, in the population taking into consideration the limitations of Table II.
- If an illegal collision is detected (case where a finger enter the object perimeter), we generate another values for the corresponding finger.
- Generate randomly initial velocity vectors $v_k, k \in \{1, 2, \dots, m\}$

Step 2. Calculate 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 $f_k = \text{fitness}(p_k), k = 1, 2, \dots, m$ where $\text{fitness}(p_k)$ represents the fitness value of the particle p_k
- Set $p_k^{pbest} = p_k$ and $f_k^{pbest} = f_k, k = 1, 2, \dots, m$
- Find the index I of the particle with best fitness value by $I = \arg(\max_{k=1}^m f_k^{pbest})$
- Set $p^{gbest} = p_I^{pbest}$ and $f^{gbest} = f_I^{pbest}$
- Set iteration = 1

Step 3. Update p_k^{pbest}, p^{gbest} and f_k^{pbest}, f^{gbest} .

- Calculate $f_k = \text{fitness}(p_k), k = 1, 2, \dots, m$ iff $f_k > f_k^{pbest}$ then set $p_k^{pbest} = p_k$ and $f_k^{pbest} = f_k$

- if $f_k^{pbest} > f^{gbest}$, $k \in \{1, 2, \dots, m\}$ then set $p_k^{gbest} = p_k^{pbest}$ and $f_k^{gbest} = f_k^{pbest}$

Step 4. Update the velocity vector v_k and the vector p_k of each particle.

$$v_k = v_k + c_1 \cdot rand() \cdot (p_k^{pbest} - p_k) + c_2 \cdot rand() \cdot (p_k^{gbest} - p_k), k = 1, 2, \dots, m$$

where $rand()$ is a function returning a random value between 0 and 1.

- $p_k = p_k + v_k, k = 1, 2, \dots, m.$
- Set $v_k = v_k \cdot w, w \in [0, 1], k = 1, 2, \dots, m$

Step 5. $iteration = iteration + 1$, if $iteration > G$ then go to Step 6, else go to Step 3

Step 6. The desired solution is the global best p^{gbest} with the best fitness value f^{gbest} .

We assume that the position of the object is reachable by the hand and the localization of the object is known. Furthermore, we will restrict our search of solution to a precise grasp which allows only contact with the fingertips.

Although, we have 21 DOF, the six DOF of the wrist is computed apart. It represents the position and orientation of the hand.

We used HandGrasp (Walha et al., 2010) to simulate the trajectories of the fingers in space. HandGrasp is an environment used for hand grasping simulation and can be expanded since it's developed under a modular architecture (Walha et al., 2011).

In our grasp strategy, the fitness function is based on a quality measure (Bicchi, 2000), (Suárez et al., 2006) associated with the position of the contact points. It takes into account the object properties as the shape, the weight, the size and the location. Park and Starr (1992) have proven that the contact points are distributed in a uniform way on the object surface, this improves the grasp stability. The quality of the grasp under this criterion, called the stability grasp index (Kim et al., 2001), is given by:

$$Q = \frac{1}{\theta_{max}} \sum_{i=1}^n |\theta_i - \bar{\theta}| \quad (7)$$

Where:

Q is the quality measure,

n is the number of fingers in contact with object,

θ_i the internal angle at vertex i of the contact polygon,

$\bar{\theta}$ is the average internal angle of the corresponding regular polygon (in degrees) :

$$\bar{\theta} = 180 \frac{n-2}{n}$$

$\theta_{max} = (n - 2)(180 - \bar{\theta}) + 2\bar{\theta}$ (in degrees), is the sum of the internal angles when the polygon has the poorest conditioned shape.

Each position of the fingertips is computed using the kinematic of the hand and in each of the iteration, the algorithm check if a contact is detected. The force of the fingers is computed using the equation:

$$\vec{F}_k = m \cdot \vec{v}_k, \quad k = 1, 2, \dots, m \quad (8)$$

Where m , is the mass of the hand.

4 EXPERIMENTATION

The experiment is computed in HandGrasp. Given a sphere with a diameter 5 cm, we run our grasp planner in order to grip this object with our simulated hand (Figure 2). The results of this simulation are shown in figure 3.

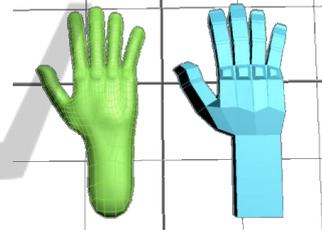


Figure 2: Simulated hand.

After 50 iterations and with 100 particles, we remark that the fingers are not all in contact with the sphere since it is not a condition in our grasp planner. In less than one second (Pentium Dual CPU, T3400 2.16 GHz * 2.16 GHz, 3 GB of RAM), the algorithm has generated the desired grasp. The second test is applied to a cube with 7 cm length (Figure 4) and the third test is for the object barrel (Figure 5).



Iteration=5 Iteration=20 Iteration=35 Iteration=50

Figure 3: Simulation results for the object sphere.



Iteration=5 Iteration=20 Iteration=35 Iteration=50

Figure 4: Simulation results for the object cube.



Iteration=5 Iteration=20 Iteration=35 Iteration=50

Figure 5: Simulation results for the object Barrel.

5 CONCLUSIONS

In this paper, a grasp planner based on a particle swarm optimization is proposed to find optimum positions of fingertips in the object, ensuring a stability of the grip. In order to guaranty a good grasp, a quality of measure function is computed. Furthermore, we restricted the limits of value for each particle so that the algorithm can generate a faster solution. Our system performs very well with simple objects.

In future works, we will adopt a multi-object particle swarm optimization (MOPSO) (Reyes-Sierra and Coello, 2006) to build a list of leaders to save the “good” grasps in a database. Then, a pareto vector is chosen based on variety of a quality of measure functions like quality based on the margin of uncertainty in the finger positions or Max-Normal-Grasping-Force quality (Liu et al., 2004).

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REFERENCES

- Agur, A. M. R. and Lee, M. J. (1999). *Grant's Atlas of Anatomy*. Lippincott Williams and Wilkins, 10th Edition.
- Bicchi, A. (2000). Hands for dexterous manipulation and robust grasping: A difficult road towards simplicity. *IEEE Trans. Robotics and Automation* 16(6), 652–662.
- 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.
- 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.
- Brand, P. W. and Hollister, A. M. (1999). *Clinical Mechanics of the Hand*. Mosby, Inc. Third edition.
- Buchholz, B. and Armstrong, T. J. (1992). A kinematic model of the human hand to evaluate its prehensile capabilities”, *J. Biomechanics*, 25 : 2, pp. 149-162.
- Buchholz, B.; Armstrong, T. and Goldstein, S. (1992). Anthropometric data for describing the kinematics of the human hand. *Ergonomics*, 35(3):261–273.
- Chesi G. and Hung Y.S. (2007). Global path-planning for constrained and optimal visual servoing, *IEEE Trans. on Robotics*, vol. 23, no. 5, pp. 1050-1060.
- Chesi G. (2009). Visual servoing path-planning via homogeneous forms and LMI optimizations. *IEEE Trans. on Robotics*, vol. 25, no. 2, pp. 281-291.
- Chinellato, E.; Morales, A.; Fisher, R. B.; and del Pobil, A. P. (2005). Visual quality measures for characterizing planar robot grasps. *IEEE Trans. Systems, Man and Cybernetics - Part C: Applications and Reviews*, 35(1), 30–41.
- Coelho, J. A. Jr. and Grupen, R. A. (1996). Online grasp synthesis. *IEEE Int. Conf. on Robotics and Automation*.
- 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.
- 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.
- Fuentes, O.; Marengoni, H. F. and Nelson, R. C. (1994). *Vision-based planning and execution of precision grasps*. TR546, Computer Science Dept., U.Rochester.
- Infantino, I.; Chella, A.; Dzindo, H. and Macaluso, I. (2003). Visual control of a robotic hand. In *IROS'2003, IEEE/RSJ International Conference on Intelligent Robots and Systems*, vol.2, no., pp. 1266-1271 vol.2, 27-31.
- Kennedy, J. and Eberhart, R. C. (1995). Particle swarm optimization. *Proceedings of IEEE International Conference on Neural Networks*, Piscataway, pp. 1942-1948.
- 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.
- Li, Y. and Pollard, N. S. (2005). A shape matching algorithm for synthesizing humanlike enveloping grasps. *Humanoids'2005, IEEE-RAS International Conference on Humanoid Robots*, Tsukuba, Japan, pp 442-449.
- Liu, G.; Xu, J.; Wang, X. and Li, Z. (2004). On quality functions for grasp synthesis, fixture planning and coordinated manipulation. *IEEE Trans. Automation Science and Engineering*, 1(2), 146–162.
- 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.
- 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.

- 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.
- 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*.
- 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.
- Pellosof, 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.
- Reyes-Sierra, M. and Coello, C. A. C. (2006). Multi-Objective Particle Swarm Optimizers: A Survey of the State-of-the-Art. *International Journal of Computational Intelligence Research*, Vol. 2, No. 3. 287-308.
- Shimoga, K. B. (1996). Robot grasp synthesis: a survey. *Int. J. of Robotics Research*, Vol.5, No.3.
- Suárez, R.; Roa, M. and Cornella J. (2006). *Grasp quality measures*. Technical University of Catalonia, Tech. Rep.
- Wagner, C. (1988). The pianist's hand: anthropometry and biomechanics. *Ergonomics* 31: 1, pp. 97-131.
- 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.
- 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.
- 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.