4-Fingered Force-Closure Grasps from surface Points Using Genetic Algorithm

Chalermsub Sangkhavijit, Nattee Niparnan and Prabhas Chongstitvatana,
Department of Computer Engineering,
Chulalongkorn University, Bangkok 10330, Thailand
Chalermsub.s@student.chula.ac.th, nattee@cp.eng.chula.ac.th, Prabhas.C@chula.ac.th

***Abstract*—This work proposes an evolutionary computation method to compute force-closure grasps from surface points. The object is presented as set of points. The proposed method searches for grasping configurations without prior knowledge of object's geometry. The experiment is carried out to validate the proposed method. The result when compared with a random search method shows that the proposed method finds more and better grasping configurations.**

I. Introduction

Robotic hand grasping is a challenging problem. Its objective is to find grasping configuration by computing the position on the object's surface that is suitable for fingers contact points. Force-closure is well understood and it is used to ensure that the object can be held securely by the fingers [1], [2]. With force-closure, a grasp can resist to the external wrench exerted on the grasped object. The well known qualitative tests for a force closure is to check that the origin of the wrench space lies exactly inside the convex hull of the primitive contact wrenches [3], [4], [5]. This is a necessary and sufficient condition. There are several approaches that represent various methods for testing that the origin is inside the convex hull [6] [7]. Majority of works in force-closure grasp computation need to know the object's shape to perform grasping with a certain class of geometric model. Most works of grasp planning focus on polyhedral models (whose all faces are planar) with the aim of analytical formulation for characterizing force-closure grasps on a given set of faces [8], [9], [10]. The problem of choosing appropriate grasped faces is rarely studied [11]. Usually, a straightforward search of all combination of faces is applied. This method will yield a time complexity problem. Thus, this method seldom applied to test objects that have more than 20 faces [12].

In general, there are many objects in the real world that can not be represented by polyhedral model with a small number of faces. A standard technique widely used in geometric modeling to represent a general shape (include curve object) is to describe the surface enclosing its volume using a large number of small triangles. Thus, it will face to handle the time problem as mentioned earlier. In [13], the problem of fixture design from a set of preselected frictionless contact points was addressed. Using a local greedy search with D-optimality criterion, the method seeks a force-closure set of 7 fixturing locations from the given set of contact points. Operation on a set of points allows dealing with the complex objects. Recently, it was suggested in [12] that acceptable force-closure grasps could be efficiently generated using a randomized selection from a set of contact candidates. The paper also attempts to convince that the resulting grasps achieve the quality comparable with human generated grasps.

This work proposed to solve the problem of force-closure grasps with 4-fingers with friction using an evolutionary technique namely Genetic Algorithm. The object is represented as set of surface points. This work is different from [14]. Our objective is not to find the best configuration. It is also different from [15], which emphasized on fast computation time. The aim of this work is to find as many configurations as possible without relying on the knowledge of geometry of the object.

II. Background

A. Basic Grasp Theory

In this section, we give some necessary background on grasping. In particular, the condition given in Proposition 1 provides the most important foundation to the derivation of our search method for finding force-closure grasps.

A hard finger in contact with some object at a point x exerts a force f with moment $x \times f$ with respect to the origin (but it cannot exert a pure torque). Force and moment are combined into a six dimensional zero-pitch wrench $w = (f, x \times f)$. Under Coulomb friction, the set of wrenches that can be applied by the finger is:

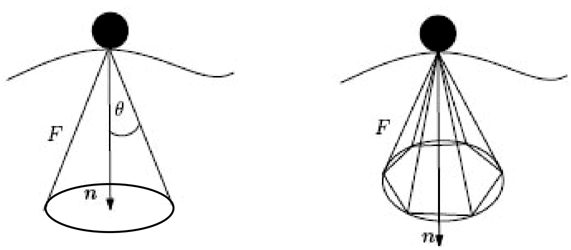
$$W = \{(f, x \times f) : f \in F\} \tag{1}$$

where F denotes the friction cone at x.

A d-finger grasp is defined geometrically by the position x_i (i = 1,…,d) of the fingers on the boundary of the grasped object. We can associate with each grasp the set of wrenches $W \subset \Re^6$ that can be exerted by the fingers. If we denote by W_i the wrench set associated with the i^{th} finger, we have

$$W = \{\sum_{i=1}^{d} w_i : w_i \in W_i \ \ for\, i = 1, \ldots, d\} \qquad (2)$$

We say that a grasp achieves *force closure* when any external wrench can be balanced by wrenches at the fingertips, i.e. when the corresponding wrench set W is equal to $\Re^6$. Because zero wrench is contained in W for a force-closure grasp, it is then clear that force closure implies equilibrium. Interestingly, it is shown in [10] that the converse of this statement is also true for non-marginal equilibrium, i.e. grasps such that the forces achieving equilibrium lie strictly inside the friction cones at the fingertips. In other word, grasps achieving equilibrium with non-zero forces for some friction coefficient achieve force closure for any strictly greater friction coefficient.



(a) *(b)*

Fig. 1. Coulomb friction: the friction cone for 3D grasps and its approximating pyramid cone.

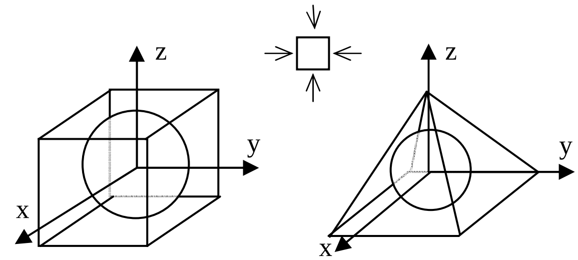
B. Quality Index

We use a quality index measure as proposed in [14]. There the quality of a grasp is defined as the length of the smallest wrench that breaks the grasp, when in every contact a force with unit strength is applied. This measure can be computed by calculating the largest inscribing ball in the grasp wrench space around the origin (see Fig. 2). It measures to what extent a grasp can resist external wrenches that are exerted on the object to be grasped without fingers starting to slide at their contact points.

In more detail on the definition, the efficient calculation and discussion about friction issues of this measure we refer to the original papers [14], [16], [17].

C. Force-closure Grasp Search

The input to the search procedure consists of a set of points on the surface of the object and corresponding inward normals at these surface points. Our objective is to search a set of given surface points for many 4-fingered frictional force-closure grasps. This is a combination problem that size of search space depends on number of given surface points and grows exponentially. Thus, a straightforward brute-force test of all combinations for force-closure condition will definitely yield unacceptable performance. In [15] it uses an aggressive pruning technique and an informed search strategy that effectively incorporates the knowledge of the force-closure condition. In this work, we use Genetic Algorithm as a search mechanism that does not need to have an addition knowledge to find solutions.



(a) *(b)*

Fig. 2. Graphic evaluation of the quality criteria: cubic and pyramid are grasping objects, grasp (a) has better quality index than grasp (b), the maximum sphere is restricted by facets around it.

III. Genetic Algorithm

GAs are search algorithms based on the mechanics of natural selection and natural genetics. They are based on the principle first laid down by Charles Darwin of survival of the most fit. First pioneered by John Holland [18]. GAs, providing robust search in complex spaces, are not affected by the complexity of the region [19].

GAs can briefly be explained in three steps. The first step is the creation of a random population where each element is coded using a specific representation that encodes a set of features defined by the problem. Second step a fitness function is used to evaluate each individual and the reproductive success varies with the fitness value. Third step two high-fitness elements are chosen for crossover and mutation. The procedure generates two new offsprings that will be the population of next generation. The process continues until population of next generation is filled up.

A. Individual Encoding

For this problem, the input is a set of points on the surface of the grasp object. Each individual represents the four grasp points and can be encoded into a four-unit chromosome which each unit represents an index of a member in the set as shown in Fig. 3. The individual's size depends on the number of members in the set. For example, if a set has 400 members, we can use 9 bits (2^9=512) to hold the index.

B. Fitness Function

GAs use fitness value as a compass to find solutions. The fitness function is defined by the problem. It is used to evaluate individuals, and decide whether it will contribute to the next generation of solutions. This criteria depends on selection scheme. We use quality index that is described previously as a fitness value.

C. Operators and Parameters

We use a simple genetic algorithm (SGA). In SGA, the number of individuals in each generation is fixed. A genetic run starts with an initial population. The first generation population is created with individuals which are generated randomly. The population is evaluated and the new population is evolved from the old population. The process is repeated until a maximum generation is reached. The parameters in SGA are: the selection type, the method of fitness scaling, the crossover type, the mutation type, the maximum generation and the population size. They are setting as follows:

Selection type: Rank selection scheme. Any population may contain more than one individual with the same score. This method will return any one of those 'best' individuals ('best' individual: the first individual in each same score group), so we do a short search here to find out how many of those 'best' there are. It uses fitness score to do the ranking and the probability of each 'best' to be chosen is equal.

Scaling: Linear scaling scheme.

Crossover type: One point crossover with probability of 0.9 (Fig. 4).

Mutation type: Flip mutation scheme with probability of 0.48. This method will pick a member in the set of surface points and then replace the mutated unit with another random point (Fig. 5).

Maximum Generation: 100

Population size: 100 chromosomes

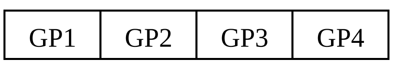


Fig. 3 Encoding scheme (GP = Grasping Point): Encoding of each individual.

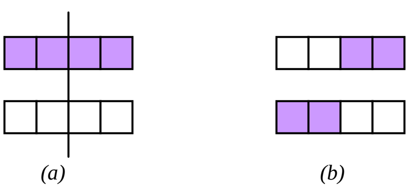


Fig. 4 One point crossover scheme: (a) selected 2 genes and random one position for crossover. (b) new 2 genes after crossover.

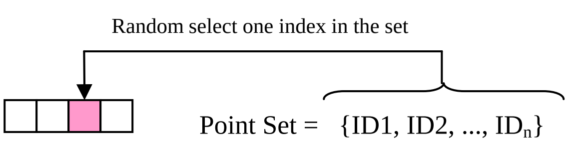


Fig. 5 Flip mutation scheme: Replace selected unit with integer index value of a random one member in the grasping point set. (ID = Index of each member in the set)

IV. Implementation and Result

We developed a program for calculating 4-finger force closure grasps from surface points using Genetic Algorithm described above. Our program is coded in C++ language using Visual C++ program and measures program processing time on an Intel CPU 3.0 GHz. computer.

In the experiment, we set the value of half angle of friction cones to 10 degrees. The experiment is carried out with three types of objects: 42-face ellipsoid, torus and duck doll (See Fig. 6). For each object, surface points are generated with random sampling with resolutions: 400, 800 and 1,200. The GA search procedure is applied. The results are compared with the results from a random search procedure. The experiment is repeated 100 times to report the average values.

Our objective is to measure number of unique solutions that satisfy force-closure grasps, the quality of their solutions and the computational time. The number of fitness evaluation is defined by the following equation.

$$\text{No. of evaluation} = \text{Population size} \times \text{No. of generation} \quad (3)$$

For each object, the results of search are shown with two measures: the number of solutions and the fitness values which represent the quality of the solutions. See Fig. 7-8, 9-10, 11-12 respectively. In all results, GA outperforms random search in both measure. Table I shows the comparison of computation time of both methods. GA is faster for an 'easy' object (42-face ellipsoid). It is slower than random search for other two objects. However, one should consider that both the quantity and the quality of the results from GA search are much better than random search.

V. Conclusion and Future works

It is possible to randomly generated many grasp candidates and try to find the force-closure grasps solutions. This method can handle the unmodeled objects and their complexity because it only deals with a set of points but it still be a combinatorial problem to choose force-closure gasp points. GA is suitable to solve problems that search space is large, complex and poorly understood. In this paper, we have presented GA to solve grasping problems versus random search method. The efficiency of the approach is confirmed by the result from the experiment. We hope that GA will be widely explored and can be adapted to these problems. Our future work will add some conditions to validate solution for real robot hands and compare GA with other efficient grasping methods.

TABLE I
WORST CASE RUN TIME AT 101,000 EVALUATION TIMES OF 1,200 SURFACE POINTS (MEASURING IN SECONDS)

Operation	42-faces	Torus	Duck doll
GA	52	112	78
Random	58	73	47

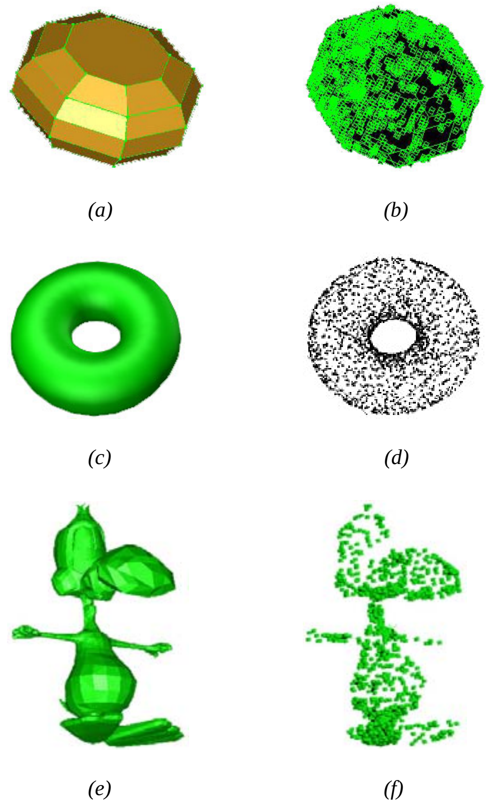


Fig. 6. Model test (a) an ellipsoid 42 faces, (b) random 1,200 surface points, (c) a torus, (d) random 1,200 surface points, (e) a duck doll, (f) random 1,200 surface points.

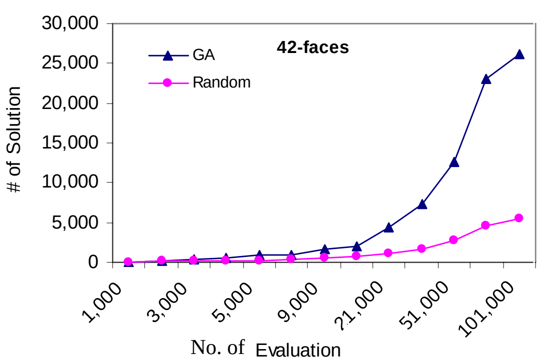


Fig. 7. Number of solutions of the ellipsoid 42 faces in Fig. 6(b).

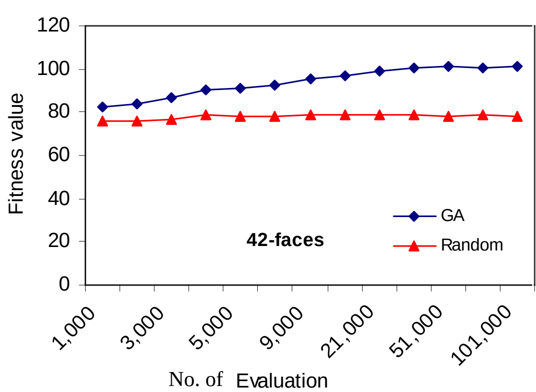


Fig. 8. Average fitness values of the ellipsoid 42 faces in Fig. 6(d).

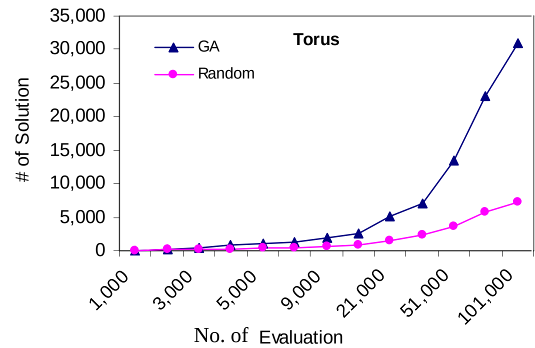


Fig. 9. Number of solutions of the torus in Fig. 6(d).

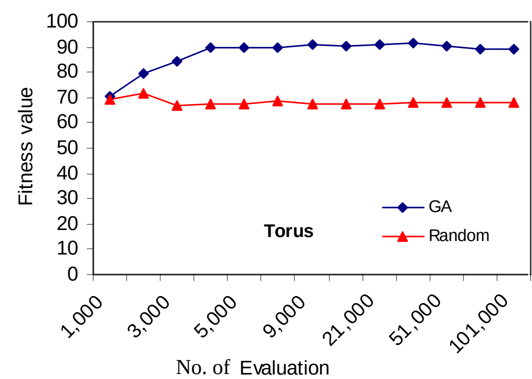


Fig. 10. Average fitness values of the torus in Fig. 6(d).

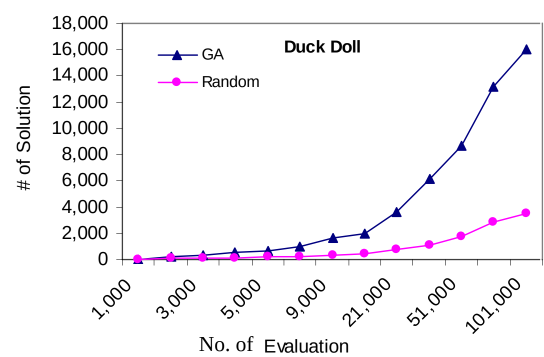


Fig. 11. Number of solutions of the duck doll in Fig. 6(f).

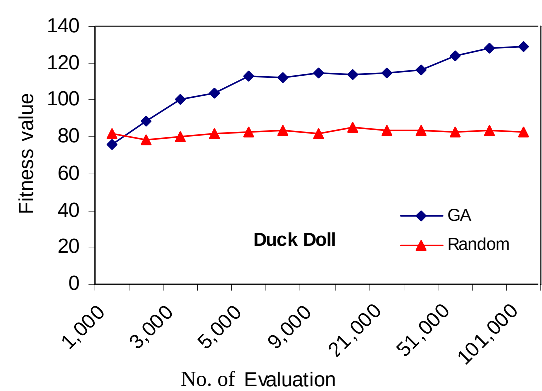


Fig. 12. Average fitness values of the duck doll in Fig. 6(f).

REFERENCES

[1] X. Markenscoff, L. Ni, and C.H. Papadimitriou, "The geometry of grasping." in International Journal of Robotics Research, pp. 61-74, February 1990.

[2] V-D Nguyen, "Constructing force-closure grasps." in International Journal of Robotics Research, pp. 3-16, June 1988.

[3] J. K. Salisbury and B. Rotch, "Kinematic and force analysis of articulated hands." ASME J. Mech., Transmissions, Automat., Design, Vol. 105, pp. 33-41, 1982

[4] K. Mulmuley, *Computational Geometry*. Prentice Hall, 1994.

[5] R. M. Murray, Z. Li and S. S. Sastry, "A Mathematical Introduction to Robotic Manipulation" CRC Press, 1994.

[6] Yun-Hui Liu and Mei Wang, "Qualitative Test and Force Optimization of 3D Frictional Force-Closure Grasps Using Linear Programming" in IEEE Int. Conf. on Robotics and Automation, Belgium, May 1998.

[7] X. Zhu and J. Wang., "Synthesis of force-closure grasps on 3-d objects based on the q distance.", in *IEEE Trans. On robotics and Automation*, pp. 669-679, 2003.

[8] A. Dandurand. "The Rigidity of compound spatial grid" Structural Topology, 10, 1984.

[9] T. Omata. "Finger Position Computation for 3-dimensional Equilibrium Grasps." in IEEE Int. Conf. on Robotics and Automation, 2000.

[10] J. Ponce, S. Sullivan, A. sudsang, J-D. Boissonnat, and J-P marlet. "On computing four-finger equilibrium and force-closure grasps of polyhedral objects." *International journal of Robotics Research*, pp. 11-35, February 1997.

[11] D. Ding, Y. Liu, M. Y. Wang, and S. Wang. "Automatic Selection of Fixturing Surfaces and Fixturing points for polyhedral workpieces." in IEEE Trans. on Robotic and Automation, 17(6), 2001.

[12] Ch. Borst, M. Fischer, and G. hirzinger. "Grasping the dice by dicing the grasp." In IEEE*/RSJ Int. Cont. on Intelligent Robots and Systems*, 2003.

[13] M. Y. Wang. "An Optimum Design for 3-D fixtures Synthesis in a point set domain." in IEEE Trans. on Robotics and Automation, 16(6), 2000.

[14] C. Ferrari and J. Canny, "Planning optimal grasps." in *IEEE Int. Conf. on Robotics and Automation*, pp. 2290-2295, France, May 1992.

[15] N. Niparnan and A. Sudsang. "Fast Computation of 4-Fingered Force-Closure Grasps from Surface Points." *in IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pp. 3692-3697, 2004

[16] Marek Teichmann and Bud Mishra, "The Power of Friction: Quantifying the "Goodness" of Frictional Grasps." In A. K. Peters, editor, Algorithms for Robotic Motion and Manipulation, pp. 311-320, A.K. Peters, Wellesley, MA, USA, 1997.

[17] Ch. Borst, M. Fischer, and G. Hizinger, "A fast and robust grasp planner for arbitrary 3d objects", in Proc. IEEE Conf. on Robotics and Automation, pp. 1890-1896, Detroit, Michigan, May 1999.

[18] J.H. Holland., *Adaptation in Natural and Artificial Systems.* University of Michigan Press, Ann Arbor, MI, USA, 1975.

[19] D.E. Goldberg, *Genetic Algorithm in Search Optimization, and Machine Learning*, Addison-Wesley Publishing, Massachusetts, USA, 1989.