Shape Nesting by Coevolving Species

Jeffrey Horn
Northern Michigan University
1401 Presque Isle Avenue
001-906-227-1607
jhorn@nmu.edu

ABSTRACT
In this paper (full version: http://cs.nmu.edu/~jeffhorn/RFS) we extend the work of [3], which introduced a new niching algorithm, resource-based fitness sharing (RFS), and demonstrated its efficacy on *shape nesting* problems. RFS was applied to the nesting of regular, convex shapes (namely, squares) within a larger, regular, convex shape (specifically, a larger square). Furthermore, the nested pieces were fixed in their orientation to be aligned with the axes of the substrate. We extend that work by applying the RFS approach to nesting of irregular, non-convex polygons, within irregular, non-convex polygon substrates, with full rotation of the pieces. The shaped pieces can be placed anywhere on the substrate, at any angle of rotation, and the task at hand is to maximize the number of such placed pieces such that no pieces overlap with each other or with the substrate boundary. We find that a single population, evolved under RFS, is able to discover a cooperative set of "species" that together "cover" most of the substrate, thus showing that the successful results reported in [3] carry over to the more general case of non-convex polygons with full rotation.

Categories and Subject Descriptors
I.2.8 [**Computing Methodologies**]: ARTIFICIAL INTELLIGENCE: Problem Solving, Control Methods, and Search – *heuristic methods.*

J.6 [**Computer Applications**]: Computer-aided Engineering – c*omputer-aided manufacturing (CAM).*

General Terms
Algorithms, Design, Experimentation.

Keywords
Genetic algorithm, evolutionary computation, niching, shape nesting, speciation, fitness sharing, coevolution, cooperative coevolution, cooperative-competitive evolution, resource sharing.

1. SHAPE NESTING
The general problem at hand involves "nesting" (that is, placing) shaped pieces on a finite substrate so as to maximize the number of such pieces on the substrate. No overlaps among the placed pieces are allowed, and all such pieces must be placed so as to be completely within the boundaries of the substrate. Shape nesting problems arise in a number of industries, such as automotive manufacturing, in which various shaped parts must be stamped from a sheet metal substrate [4].

GECCO'05, June 25-29, 2005, Washington, DC, USA.
ACM 1-59593-010-8/05/0006.

2. THE RFS ALGORITHM
Resource sharing seems to be nature's way to induce speciation (niching) during evolution, but it appears to induce complex dynamics [2]. Horn [3] proposed *resource-based fitness sharing* (RFS). RFS handles explicit resources while keeping the equilibrium calculations simple (linear), as in fitness sharing [1]. The result is an algorithm with the natural fit of resource sharing, and the speed and simplicity of fitness sharing.

The implementation of RFS is the same as used in [3]. For the two dimensional shape nesting problem, the *placement* of a piece is made by specifying the piece's *location* and its *orientation* (rotation), as in Figure 1. Thus a chromosome consists of three genes: x,y,Θ.

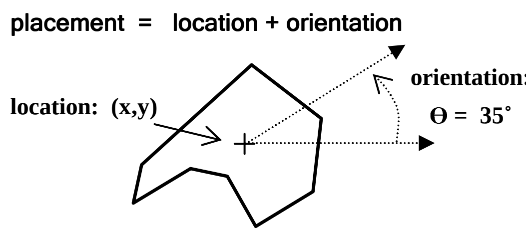

Figure 1. Shape nesting decision variables.

To focus our experiments on selection, we limit ourselves to one discovery operator: mutation. In particular, we use the same Gaussian mutation as in [3]. Each generation, with a probability p_m = 0.01 (per allele), the x and y coordinates of an individual, and its orientation Θ, are independently adjusted by a pseudo-random amount, normally distributed around a mean of 0.

Every individual of the current population is evaluated and assigned a "fitness". Pieces that extend beyond the boundaries of the substrate are given a fitness of 0. For all other individuals the algorithm calculates a *shared fitness* for use in a standard selection method. In RFS, the shared fitness for each individual is a function of the area of the individual piece (e.g., f_A and f_B in Figure 2) and the extent to which the placed piece overlaps with other placed pieces (e.g., f_{AB} in Figure 2).

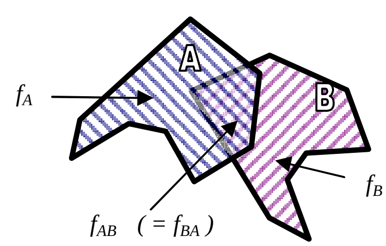

Figure 2. Defining terms for RFS.

We consider a *species* to be a set of identical individuals (i.e., with identical placements). Thus unique chromosomes (x,y,Θ) map one-to-one with unique species. There is complete overlap between any two members of the same species, while there is less than complete overlap between any two members of different species. The shared fitness, under RFS, for every member of a species X is given by

$$f_{Sh,X} = \frac{f_X}{\sum_{\forall \text{ species } Y} n_Y \, f_{XY}} .$$

The numerator f_X is the "objective" fitness of the individual (species) X. The denominator is the "niche count" for X in the current population. The niche count is a sum of pair-wise interactions between the individual (being evaluated) and each of all the other individuals in the current population. The *species count* n_Y is simply the number of members of species Y in the current population. For example, the RFS shared fitness calculation for the two species A, B in Figure 2 would be

$$f_{Sh,A} = \frac{f_A}{n_A f_A + n_B f_{AB}}, \qquad f_{Sh,B} = \frac{f_B}{n_B f_B + n_A f_{AB}}.$$

3. EXPERIMENTS

We use a population size of M = 6000, a fairly high mutation probability p_m = 0.20 (per allele), binary tournament selection with continuously updated sharing (see [5]), and random initial populations (generation 0). In Figure 3 (top) we see generation 1 of the first experiment. Many of the "infeasible" species from generation 0 have been eliminated.

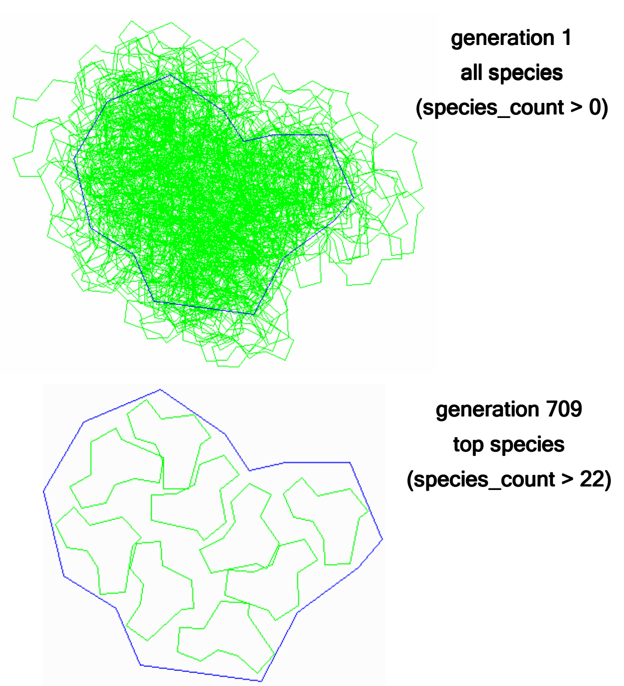

Figure 3. Experiment 1.

By generation 709 (Figure 3, bottom), the algorithm seems to have "settled" on a particular ensemble of 9 species (the figure depicts only those species with species count greater than 22).

Figure 4 shows the result of Experiment 2. Here the population size was set to M = 500 and the mutation rate was p_m = 0.30. The figure shows all species with counts of at least 19 in generation 4700. (It is not known if this is an optimal solution, as the amount of unused substrate exceeds the area of a sixth piece.)

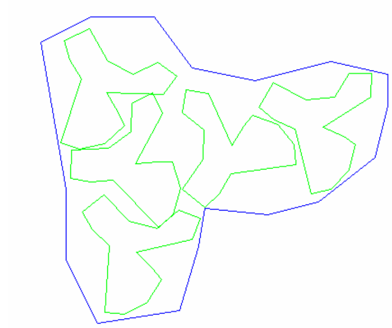

Figure 4. Experiment 2.

4. CONCLUSIONS

The RFS approach shows promise for general shape nesting problems. The combination of resource-based fitness sharing with GA selection seems able to promote competition among cooperative subsets of individuals within a single population. Other discovery operators (e.g., crossover) combined with this particular selection pressure might find even better cooperative ensembles more quickly and on harder problems, including real-world shape-nesting problems from various industries.

5. REFERENCES

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