

Introduction

The purpose of conducting these experiments is to better understand and acquire a ‘feel for’ the local search evolutionary algorithm. The objective was to answer the questions of *how* each binary encoding and mutation operator affects the result of the algorithm (the fitness), and *why*. Following this are the analysis of the results of my C++ implementation for each combination of encoding/operator.

Methods

Note: Results are a few example runs formatted as such:

- 1st column = Number of evaluations to reach best fitness
- 2nd column = Number of improvements made to reach best fitness
- 3rd column = Best fitness reached

These are followed by the mean and standard deviation for each column for 1000 runs of the method, and the number of unique optima found for the method.

Plain encoding – Random Jump (0 0)

This performed surprisingly well. My hypothesis is that the large number of evaluations allowed random jumping to fully utilize its strength of the entire search space being its local neighborhood.

1455	11	0.992480	col	Mean	Stddev
4293	9	0.987311	1	4820.22	2873.37
9866	9	0.998121	2	9.66	2.71
3594	16	0.993120	3	0.99	0.01
671	7	0.992932	Num unique optima found: 302		

Grey encoding – Random Jump (1 0)

Under Grey encoding, random jump performed essentially the same, as the encoding did not significantly affect the purely random nature of the mutation.

6033	14	0.997094	col	Mean	Stddev
3903	11	0.991802	1	4923.25	2944.82
4335	9	0.995880	2	9.79	2.95
3794	9	0.995652	3	0.99	0.01
3757	15	0.970609	Num unique optima found: 296		

Plain encoding – Bit Flip (0 1)

Random bit flipping also performed very well over a large number of evaluations, like random jumping. However, the average number of improvements it made was higher and had greater variation than that of random jumping, as well as ~25% more unique local optima. Since it changes a single bit, the neighborhood is only the possible values resulting from a single changed bit, not the entire search space like random jumping. Therefore, it was able to “hit” more local optima on its way to best fitness.

121	7	0.990038	col	Mean	Stddev
2432	10	0.998693	1	4826.79	2877.22
2337	12	0.998540	2	14.7	5.26
6352	10	0.997855	3	0.99	0.01
8972	15	0.987535	Num unique optima found: 407		

Grey encoding – Bit Flip (1 1)

The number of improvements and evaluations made on average was slightly higher than for plain encoding, with slightly less local optima found. This is a result of the Grey encoding affecting the range of the neighborhood, making it easier to skip over local optima, thus taking slightly longer to reach best fit.

1001	12	0.989701	col	Mean	Stddev
8141	16	0.983858	1	5152.28	2855.5
4818	11	0.998540	2	15.62	5.64
8191	20	0.961796	3	0.99	0.01
2037	11	0.970537	Num unique optima found: 397		

Plain encoding – Single-Dimension Increment/Decrement (0 2)

This mutation had terrible fitness performance under plain encoding. Due to its limited neighborhood, it was getting easily stuck on local maxima with no way out, which is why there were so many local optima found throughout the runs. (997 out of 1000 runs)

7369	81	0.014650	col	Mean	Stddev
3956	59	0.012469	1	4898.45	3461.13
2910	56	0.016069	2	96.59	70.4
501	60	0.021563	3	0.09	0.17
968	18	0.064953	Num unique optima found: 997		

Grey encoding – Single-Dimension Increment/Decrement (1 2)

Under Grey encoding, however, it performed much better. While the size of the neighborhood remained the same, the range of it was greater. The greater mobility afforded by this increased range allowed it to converge much faster, due to not getting stuck on local optima “ruts” as often.

5034	23	0.023071	col	Mean	Stddev
5445	24	0.015314	1	4876.86	3229.38
2102	18	0.192070	2	23.04	12.58
2038	18	0.017801	3	0.13	0.22
5459	61	0.116256	Num unique optima found: 849		

Conclusions

Grey encoding seemed to only significantly affect the single-dimension increment/decrement operator. My conclusion was that how much it affected an operator was dependent on how large of a neighborhood the operator had, and how random the operator was. If it had a neighborhood the size of the search space, in the case of random jump, then it hardly affected it, while it significantly affected the small neighborhood of SD Inc/Dec.

For the operators, the neighborhood size mattered, as the operator with the largest neighborhood (random jump) converged on an optimal solution in the smallest number of improvements, while the smallest (sdIncDec) took the most.