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PSO Parameters Configurations

Particle Swarm Optimization can be used to solve different equations and problems, in the case for this experiment, the focus was Rastrigin Function, to compare how the parameters affect the results of the problem.

To start off, a simple vanilla PSO program was created, using the provided pseudo code. The program allows users to enter their own values number of iterations, number of particles, number of dimensions and of course the values for each parameter. From there, the program generates randomly positioned particles, evaluates their fitness according to the Rastrigin Function and updates their velocity and position according to their respective equations. These equations are where the parameters come into play. The parameters are omega (ω), coefficient one (c1) and coefficient two (c2). To update the velocity, the equation is the sum of three different parts; inertia term(ωvi(t)) , cognitive term (c1r1(y(t) xi(t))), social term (c2r2(ˆy(t) xi(t))). Once the velocity is updated with these terms, the position is updated as well, with the equation xi(t + 1) = xi(t) + vi(t + 1). Thus, the parameters affect both the velocity and new position of the particles.

To see the affect of the parameters on the fitness of particles, four different sets of parameters were used with a consistent amount of iterations (500 iterations), particles (30 particles) and dimensions (35 dimensions). For each set of parameters, the PSO algorithm was used five times to find the average position and fitness of the global best particle. The results of these calculates are available on the tables at the end of the report.

The first set of parameters are the Van Den Bergh parameters (ω = 0.729844 and c1=c2 = 1.496180). Generally, these parameters lead the algorithm to convergence, and perform the best. For these experiment, these were not the best parameters, but very close to the best (second best). The results for these parameters for each run were similar and around the same range. Due to the fact that this simulation only ran 500 iterations with 30 particles, there is room for deviation. Perhaps with more iterations (around 5000), this would have been the most optimal result or with more runs. Overall, it showed that the Van Den Bergh parameters give an optimal result.

The second set of parameters were ω = 0.4 and c1=c2 = 1.2. These parameters had omega at a higher range and the coefficients are little over the mid-range. Generally, omega is between -1 and 1, while the coefficients are between 0 and 2. The results of this set were the best, with the lowest fitness. These results were very close to the results of the Van Den Bergh parameters, the Van Den Bergh omega is also close to higher range, while the coefficients are at a higher mid-range. Thus, a value a bit higher than the mid-range of the coefficients and a high omega value leads to optimal results.

The third set of parameters were ω = 1 and c1=c2 = 2. Here the parameters were at their max range, and performed worse than the other two parameters discussed so far. This shows that the extreme range of the parameters does not lead to the most optimal results.

The fourth and last set of parameters were also the extreme cases of omega and the coefficients, with ω = -1 and c1=c2 = 2. Here omega was at its lowest range, while the coefficients at their greatest range. This set of parameters had the worst result overall, thus showing that opposite extreme values of the parameters (huge different between omega and the coefficients) is the least optimal set of parameters.

At the end of the experiment, it is clear that the Van Den Bergh parameters, along with other parameters with omega near its higher range with the coefficients at a mid-high range give the most optimal results. While, parameter values at the extremes of their ranges give the least optimal results. Additionally, it is interesting to note how a small change in the parameters (such as omega from 0.729844 to 1 and the coefficients from 1.496180 to 2 can affect the overall fitness.

In conclusion, the parameters play a key role in contributing to the fitness of particles in a PSO algorithm. To further explore the Particle Swarm Optimization algorithm and its results, the difference in iterations, number of particles and dimensions can be experimented.

Appendix:

Table 1: Average Comparison Between Global Best's Positions With Different Parameters

POSITION COMPARISON (X value)	Run 1	Run 2	Run 3	Run 4	Run 5	Average of 5 Runs
ω = 0.729844, c1 = c2 = 1.496180	0	3	2	4	2	2.2
ω=0.4,c1=c2=1.2	1	1	4	0	1	1.4
ω=1.0,c1=c2=2.0	2	2	3	2	4	2.6
ω=−1.0,c1=c2=2.0	4	1	4	4	1	2.8

Table 2: Average Comparison Between Global Best's Fitness With Different Parameters

FITNESS COMPARISON	Run 1	Run 2	Run 3	Run 4	Run 5	Average of 5 Runs
ω = 0.729844, c1 = c2 = 1.496180	241	302	313	247	310	282.6
ω=0.4,c1=c2=1.2	284	274	310	282	258	281.6
ω=1.0,c1=c2=2.0	249	313	278	284	322	289.2
ω=−1.0,c1=c2=2.0	372	285	317	293	260	305.4