Laser Pulse Shaping problem Practical Assignments Natural Computing, 2009

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1 Introduction

The report is focused on the so-called *laser pulse shaping problem*. Today's lasers are also used within the range of atoms or molecule research. Using small pulses it is able to align and alter the movement of the atoms.

The problem lies in the fact the atoms cannot be controlled by any type of laser pulse. There are many parameters which could all be set to 'shape' the laser pulse the way it can move the atoms.

To turn and tweak all the 'knobs' at the same time there will be *Particle* Swarm Optimizer (PSO) used to explore the search space. The PSO is basically a whole bunch of individual agents which all try to find an optimum into the search space. During this search they get input about other potential bests from the whole swarm (broadcast style) and the neighborhood (observation) and using this values they determine their new location.

2 Problem description

A laser pulse going through a crystal produces light at the octave of its frequency spectrum. The total energy of the radiated light is proportional to the integrated squared intensity of the primary pulse. Explicitly, the timedependent profile of the laser field in our simulations is given by:

$$E(t) = \int_{-\infty}^{\infty} A(\omega) exp(i\phi(\omega)) exp(i\omega t) d\omega, \qquad (1)$$

where $A(\omega)$ is a Gaussian window function describing the contribution of different frequencies to the pulse and $\phi(\omega)$, the phase function, equips these frequencies with different complex phases.

To determine the best solution a fitness function is needed, which could be found in the shape of equation 2

$$SHG = \int_0^T E^4(t)dt \longrightarrow maximization \tag{2}$$

Note that 0 < SHG < 1

3 Statistics

4 Approach

The Wikipedia page 'Particle swarm optimization' ¹ contained a reference implementation used to implement the algorithm. The nice part about the algorithm is its flexibility in tuning. As within the *PSO* there are many 'knobs' which could be tweaked as well, like likeliness of heading for the global optimum, neighborhood optimum and local optimum.

5 Implementation

The code is written in $Octave^2$ which is the open-source 'variant' of $MAT-LAB \odot^3$. There are small minor differences between them, but all code is made compatible to to run on both systems. The code is to be found in Appendix 8.

As work is done remotely, the following commands are used:

```
matlab-bin -nojvm -nodesktop -nosplash -nodisplay < %%PROGRAM%%
octave -q %%PROGRAM%%</pre>
```

The flock is represented into a 3d block. A slice of that block contains a local swarm, a column in slice is a individual particle.

6 Results

The program is run against a parameter set of 80. The algorithm is allowed to run for 10 minutes with a maximum of 1000 iterations. If there are no improvements after 5 iterations then it will bail out as well.

 $^{^{1}} http://en.wikipedia.org/wiki/Particle_swarm_optimization$

²http://www.gnu.org/software/octave/

³http://www.mathworks.com/products/matlab/

The algorithm is kind of 'social' e.g. it will favor the neighborhood and the global optimum more than it's own local optimum. Also its active, meaning it changes direction fast the moment the optimum is found somewhere else.

Size of the local swarms is 50, each with 10 agents.

After running 5 times, the best fitness found was 0.0000045481. Improvement is almost only shown in the first 100 iterations see figure 1a, afterwards it quickly stalls. Trying with a smaller number more and less show the same result as seen in figure 1b



Figuur 1: Fitness throughout the iterations

Changing various flags like walkspeed *wander* or changing the socialness of the agents does not prove to change much in the algoritm result.

7 Conclusions

Giving the lack of external results of other algorithms in large scale setups (80 parameters) its hard to say whether this is a good or worse preforming algorithm.

For further research within the algorithm there are many knobs to tweak as well. One could think of implementing a algorithm around this setup as well. 8 Appendix 1

```
1 % Particle Swarm optimalisation
  2 % BSDLicence
  3 % Rick van der Zwet - 0433373 - <hvdzwet@liacs.nl>
  4 % Modeled after http://en.wikipedia.org/wiki/Particle_swarm_optimization
 6 % Dimention settings
 7 parameters = 10;
 8
 9 % If global optimum does not change this many steps bail out
 10 iteration_break = 5;
 11 max_iterations = 1000;
 12 max_time = 10 * 60; % in sec
 13
 14 % Flock properties
 15 local_swarm_size = 50;
 16 local_swarms = 10;
 17
 18 %% Particle properties
 19 % Speed of walking around to a certain direction
 20 wander = 0.4;
 21
 22 % 'Influence' of the envirionment with regards to solutions
 23 % Trust the group global solution to be feasible
 24 \text{ c_social} = 0.4;
 25 % Trust the neighbor solution to be feasible
 26 \text{ c_cognitive} = 0.4;
 27 % Trust the own best solution to be feasible
 28 \text{ c_ego} = 0.2;
 29
 30 % Variables used for plotting
 31 fitness_history = [];
 32 fitness_iterations = [];
 33
 34 % Initiate all particles
 35 flock_p = rand(parameters,local_swarm_size,local_swarms) .* (2
* pi);
 36 flock_v = zeros(size(flock_p));
 37
 38
 39 % Global best placeholder
 40 g_best = ones(parameters,1) .* 9;
```

```
41 g_fitness = 0;
42 % at (:,x) lives the neighbor best of local_swarm 'x'
43 n_best = ones(parameters,local_swarms) .* 9;
44 n_fitness = zeros(parameters,local_swarms);
45 % at (:,p,x) leves the local best of particle 'p' in local_swarm
'x'
46 l_best = ones(parameters,local_swarm_size,local_swarms) .* 9;
47 l_fitness = zeros(local_swarm_size, local_swarms);
48
49 idle_counter = 0;
50 tic();
51
52 % Code not optimised for performance, but for readablility
53 for i = 1:max_iterations
        for s = 1:local_swarms
54
            fitness = SHGa(flock_p(:,:,s));
55
56
            % See if we got any better local optimum
57
            for p = 1:local_swarm_size
58
                if fitness(p) > l_fitness(p,s)
                    l_fitness(p,s) = fitness(p);
59
                    l_best(:,p,s) = flock_p(:,p,s);
60
61
                end
62
            end
63
64
            % See if we got any better neighbor optimum
            for p = 1:local_swarm_size
65
                if l_fitness(p,s) > n_fitness(s)
66
                    n_fitness(s) = l_fitness(p,s);
67
68
                    n_best(:,s) = l_best(:,p,s);
69
                end
70
            end
71
        end
72
73
        idle_counter = idle_counter + 1;
74
75
        % See wether we have a new global optimum
        for s = 1:local_swarms
76
77
            if n_fitness(s) > g_fitness
78
              g_fitness = n_fitness(s);
79
              g_best = n_best(:,s);
80
              idle_counter = 0;
```

```
81
            end
 82
        end
 83
 84
        % Stop conditions
 85
        if idle_counter == iteration_break
            fprintf('Caught by idle_counter\n');
 86
 87
            break;
 88
        end
 89
        if toc > max_time
 90
            fprintf('Caught by max_time used \n');
 91
            break;
 92
        end
 93
 94
 95
        fprintf('%04i : %.15f\n', i, g_fitness);
        fitness_iterations = [fitness_iterations, i];
 96
 97
        fitness_history = [fitness_history, g_fitness];
 98
99
100
        % Update particles to new value
101
        r_cognitive = rand();
102
        r_social = rand();
103
        r_ego = rand();
        for s = 1:local_swarms
104
105
            for p = 1:local_swarm_size
                flock_v(:,p,s) = flock_v(:,p,s) * wander + ...
106
                   (g_best - flock_p(:,p,s)) * (c_cognitive * r_cognitive)
107
+ ...
                   (n_best(:,s) - flock_p(:,p,s)) * (c_social * r_social)
108
+ ...
                   (l_best(:,p,s) - flock_p(:,p,s)) * (c_ego * r_ego);
109
110
                flock_p(:,p,s) = flock_p(:,p,s) + flock_v(:,p,s);
111
            end
112
        end
113 end
114
115 % Dispay hack
116 g_fitness
117 g_best
118
119 plot(fitness_iterations,fitness_history);
```

```
120 title(sprintf('Particle Swarm Optimalisation on Laser-Pulse shaping
problem')) )
121 ;
122 ylabel('fitness');
123 xlabel('iterations');
124 grid on;
125 legend(sprintf('Parameters %i',parameters));
126 print(sprintf('pso-fitness-%.10f.eps', max(fitness_history)),'-depsc2');
```

```
1 % Particle Swarm optimalisation
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3 % Rick van der Zwet - 0433373 - <hvdzwet@liacs.nl>
4 % Modeled after http://en.wikipedia.org/wiki/Particle_swarm_optimization
5
6 % Iterate on multiple vectors
7 function fitness = SHGa(v)
8 for i = 1:length(v(1,:))
9 fitness(i) = SHG(v(:,i));
10 end
11 end
12
```

```
2 % This function calculates the Second Harmonic Generation
3 % of a Gaussian of frequencies with a given phase function.
4 %
5 %
       phi - an input COLUMN vector, containing the phase function.
6 %
       SHG - the output of the calculation; scalar.
8
9 function [SHG] = SHG(phi);
10
11 % constant for consistency with the Fortran Calculation...
12 c_fortran = 153.7687;
13
14 % Generate the Gaussian and the phase function consistently.
15 Np = length(phi(:,1));
16 \text{ Nv} = 4000;
17 v = linspace(-300,300,Nv); %Linearly Spaced Vector
18 G = 40;
19 Ain = \exp(-(v/G)^2); %The Gaussian of Frequencies
20
21 %Distribute the phase function according to the desired resolution
22 step = round((2600-1400)/Np);
23 step = step + (step==1);
24 phase = zeros(1,Nv);
25 k = 1;
26 for j = 1400:step:2600-step+1,
      phase([j:j+step-1]) = phi(k);
27
28
      if (k < Np)
29
         k = k+1;
30
      else
31
         k = Np;
32
      end
33 end
      % *** The Core: SHG *** %
34
35
36 %Fourier Transform with phase shift (phi) on the Gaussian *Ain*
37 E_t = fftshift(ifft(fftshift(exp(i*phase).*Ain)));
38
39 %plot(abs(E_t));
40 %Integrate the result to yield the SHG
41 SHG = sum(abs(E_t).^4)/c_fortran;
```