A Procedure for Designing a Patch Antenna using Multi-level Boolean Particle Swarm Optimization

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1. Introduction

Optimization is one of the most important problems in engineering. There are various optimization techniques; one of which is particle swarm optimization. It was first introduced in [1].

Recently, an application of particle swarm optimization in antenna engineering was demonstrated in [2]. Marandi [3] introduced an application of Boolean particle swarm optimization to designing a dual-band planar antenna. Detailed discussion on Boolean particle swarm optimization is available in section 2. Later, Duvigneau [4] presented an application of multi-level swarm optimization to Aerodynamic shape optimization. Modified from [4], this paper presents a procedure for designing a patch antenna using multi-level Boolean particle swarm optimization. Multi-level Boolean particle swarm optimization is a further development of Boolean particle swarm optimization and inspired by multigrid method; Multigrid method [5] is a well-known numerical technique for accelerating the rate of convergence in solving linear system equations using iterative methods.

2. Boolean Particle Swarm Optimization (BPSO)

Particle swarm optimization is an evolutionary computation technique based on the movement and intelligence of swarms. The optimization is initialized with a random swarm of particles (a population of potential solutions) $x_1(0)$, $x_2(0)$,…, $x_n(0)$. Each particle flies through the search space with velocity adjusted by 3 factors:

1. Inertia factor: This factor prevents each individual particle from drastically changing in direction.
2. Cognitive factor: The effect of this factor is that each individual particle is drawn back to its local best position ($p_{best,i}$)
3. Social factor: The effect of this factor is that each individual particle (potential solution) is drawn towards the global best position (g_{best}) found by the whole population of particles.

The local best position ($p_{best,i}$) and the global best position (g_{best}) refer to the best position fittest to the so-called "fitness function" found by each individual and by the whole swarm of particles, respectively. The fitness function corresponding radiation characteristics can be evaluated by solving for current on the patch antenna; Radiation characteristics can then be calculated directly from the current. So is the fitness function. There are various numerical techniques for solving current; one of which can be found in [8].

There are various variations of particle swarm optimization. Further detailed discussion can be found in [2]-[4] and [6]-[7]. Only Boolean particle swarm optimization which is used for discussion in this paper is presented.

The velocity of particle i at generation $t+1$, denoted by $v_i(t+1)$, can be expressed as

$$v_i(t+1) = \omega . v_i(t) + c_1.(p_{best,i}(t) \oplus x_i(t)) + c_2.(g_{best}(t) \oplus x_i(t)) \tag{1}$$

The velocity consists of three components: the inertia component $\omega v_i(t)$, the cognitive component $c_1(p_{best,i}(t) \oplus x_i(t))$ and the social component $c_2(g_{best}(t) \oplus x_i(t))$. These components are associated with the inertia factor, the cognitive factor and the social factor, respectively. It should be noted that ω, c_1 and c_2 are random binary numbers.

The position of particle i at generation $t+1$, denoted by $x_i(t+1)$, can be expressed in terms of the position and velocity of particle i at the previous generation as shown in eq. (2)

$$x_i(t+1) = x_i(t) \oplus v_i(t) \tag{2}$$

The search algorithm of particle swarm optimization is shown as follows:

$t = 0$
% $x_i(0)$ and $v_i(0)$ are the position and velocity, respectively, of particle *i*, $i = 1, 2, \ldots, n$ at generation $t = 0$.
Initialize $x_1(0), x_2(0), \ldots, x_n(0)$
Set $v_1(0), v_2(0), \ldots, v_n(0) = \underline{0}$
% $f\left(x_1(0)\right)$ is the fitness function evaluated for particle 1 at generation $t = 0$.
Evaluate $f\left(x_1(0)\right)$
$p_{best,1} = x_1(0)$
$g_{best} = x_1(0)$
for $i = 2$ to n
Evaluate $f\left(x_i(0)\right)$ % $f\left(x_i(0)\right)$ is fitness function evaluated for particle *i* at generation $t = 0$
    if $f(p_{best,i}) < f(g_{best})$
        $g_{best} = p_{best,i}$
    end if
end for

while (stop = false)
    for i = 1to n
        Random ω, c_1 and c_2
        $v_i(t+1) = \omega . v_i(t) + c_1 .(p_{best,i}(t) \oplus x_i(t)) + c_2 .(g_{best}(t) \oplus x_i(t))$
        $x_i(t+1) = x_i(t) \oplus v_i(t+1)$
        Evaluate fitness function $f(x_i(t+1))$
    if $f(x_i(t+1)) < f(p_{best,i})$
        $p_{best,i} = x_i(t+1)$
    end if
    if $f(p_{best,i}) < f(g_{best})$
        $g_{best} = p_{best,i}$
    end if
end for
$t = t+1$
end while

2. Coding of a Patch Antenna

For the purpose of coding, consider a patch antenna for various levels. At level $L = 1$, the patch antenna is divided into cells of N rows and N columns with equal dimensions. Each individual cell is represented by a binary random number “1” or “0”. “1” represents the presence of associated patch cell whereas “0” represents the absence of associated patch cell. At level $L = 2$, each individual cell is subdivided into cells of N rows and N columns with equal dimensions. Consequently, a binary random number “1” becomes N^2 binary random numbers “11...1” whereas a binary random number “0” becomes N^2 binary random numbers “$00...0$”. For further level L (> 2), each individual cell is subdivided into cells of N rows and N columns with equal dimensions. Consequently, a binary random number “1” becomes N^2 binary random numbers “$11...1$” whereas a binary random number “0” becomes N^2 binary random numbers “$00...0$”.

Figure 1 shows the patch antenna is divided into cells of N rows and N columns with equal dimensions. For the sake of simplicity, assume that N = 3. Hence, at level L = 1, each individual cell is represented by a binary random number “1” or “0”. “1” represents the presence of associated patch cell whereas “0” represents the absence of associated patch cell. At level L = 2, each individual cell is subdivided into cells of 3 rows and 3 columns with equal dimensions. Consequently, a binary random number “1” becomes 9 binary random numbers “$11...1$” whereas a binary random number “0” becomes 9 binary random numbers “

3. Multi-Level Boolean Particle Swarm Optimization

The use of multi-level Boolean particle swarm optimization developed from [8] is based on the idea that the information collected from a given level is transferred to the next level. That is, the local best positions ($p_{best,i}$) and global best position (g_{best}) from a given level is transferred to the next level.

The search algorithm of multi-level Boolean particle swarm optimization is shown as follows:

t = 0
% $x_i(0)$ and $v_i(0)$ are the position and velocity, respectively, of particle i, i = 1, 2,…, n at generation t = 0.
Initialize $x_1(0), x_2(0),\ldots, x_n(0)$
Set $v_1(0), v_2(0),\ldots, v_n(0) = \underline{0}$
% $f\left(x_1(0)\right)$ is fitness function evaluated for particle 1 at generation t = 0.
Evaluate $f\left(x_1(0)\right)$
$p_{best,1} = x_1(0)$
$g_{best} = x_1(0)$
for i = 2 to n
% $f\left(x_i(0)\right)$ is fitness function evaluated for particle i at generation t = 0.
Evaluate $f\left(x_i(0)\right)$
    if $f(p_{best,i}) < f(g_{best})$
        $g_{best} = p_{best,i}$
    end if
end for
for L = 1:L_{max}
if L > 1
    Initialize $x_1(t), x_2(t),\ldots, x_n(t)$
    Set $v_1(t), v_2(t),\ldots, v_n(t) = \underline{0}$
end
while (termination stop at level L = false)
    for i = 1to n
        Random ω, c_1 and c_2
        $v_i(t+1) = \omega.v_i(t) + c_1.(p_{best}(t) \oplus x_i(t)) + c_2.(g_{best}(t) \oplus x_i(t))$
        $x_i(t+1) = x_i(t) \oplus v_i(t+1)$
        Evaluate fitness function $f(x_i(t+1))$
    if $f(x_i(t+1)) < f(p_{best,i})$
        $p_{best,i} = x_i(t+1)$

end if
if $f(p_{best,i}) < f(g_{best})$
$g_{best} = p_{best,i}$
end if
end for
$t = t + 1$
end while
if $L < L_{max}$
Transfer $g_{best}, p_{best,1}, \ldots, p_{best,n}$ **from the present level to the next level**
end
end for

4. Conclusion

The development of Multi-level Boolean particle swarm optimization is inspired by multigrid method. It is based on the idea that past experience of the swarm of particles can be transferred from the present level to the next level. By the fact that Boolean particle swarm optimization at the lower level requires less computational time than that at the higher level. Therefore, Multi-level Boolean particle swarm optimization is more efficient than Boolean particle swarm optimization.

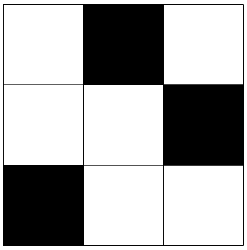

Figure 1: Patch Antenna is represented by binary numbers “010001100” at level L = 1 whereas at level L = 2 each individual binary number “1” is replaced by “111111111” and each binary number “0” is replaced by “000000000”.

References

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