

## RESEARCH ARTICLE

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# Photodynamic Cancer Therapy Using Wavelet Based Monte Carlo Computation of Light Absorption with a Genetic Algorithm

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### Abstract

**Objective:** The method to treating cancer that combines light and light-sensitive drugs to selectively destroy tumour cells without harming healthy tissue is called photodynamic therapy (PDT). It requires accurate data for light dose distribution, generated with scalable algorithms. One of the benchmark approaches involves Monte Carlo (MC) simulations. This gives an accurate assessment of light dose distribution, but is very demanding in computation time, which prevents routine application for treatment planning. **Methods:** In order to resolve this problem, a design for MC simulation based on the gold standard software in biophotonics was implemented with a large modern wavelet based genetic algorithm search (WGAS). **Result:** The accuracy of the proposed method was compared to that with the standard optimization method using a realistic skin model. The maximum stop band attenuation of the designed LP, HP, BP and BS filters was assessed using the proposed WGAS algorithm as well as with other methods. **Conclusion:** In this paper, the proposed methodology employs intermediate wavelets which improve the diversification rate of the charged genetic algorithm search and that leads to significant improvement in design effort efficiency.

**Keywords:** Cancer therapy- skin treatments- biophotonics- wavelet- tissue optical- FIR filter- accuracy

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### Introduction

Photodynamic therapy (PDT) is being tested in the clinic treatment that involves the administration of a nontoxic drug that settles in tumor cells (Dougherty, 1993), followed by the application of laser light to the tumor, thereby activating the drug and killing the cancer. This technology can only treat areas where light can reach (Dougherty et al., 1978; Saini et al., 2016). So, it's mainly used to treat problems on or just under the skin, or in the lining of organs that can be reached with a light source. Moreover, PDT is also tested against pre-cancers in the mouth and other places. An effectiveness of the treatment can be improved by conforming the light dose (photon fluence) contour lines to the shape of the clinical target volume. One of the most scalable, random sampling, and accurate method to compute the fluence distribution is the Monte Carlo (MC) method. It calculates the primary fluence distribution of the millions of proton beam (Fanti et al., 2006; Wang et al., 1995). However, method of PDT treatment planning is an iterative process and involving multiple parameters. Obviously, this is time-consuming process and this problem is compounded. It highlights the essence for speeding up the light dose computation to depict the use of MC-based models for clinically

robust PDT treatment planning (Gokhale et al., 2004). A statistical-based algorithm used in radiation dose calculations on an evolutionary approach obtained a low accuracy. However, they incorporate a very different design flow with the use of FIR filter (Chitode, 2009). Efforts to speed up MC simulations for tissues modeling light propagation have been mostly limited to software parallelization process.

In general, photodynamic therapy for skin cancer diagnoses is a Non deterministic Polynomial (NP) hard problem. To resolve this issue, deterministic approaches usually are not able to provide a exact solutions. On the other hand nature inspired meta-heuristic optimization approaches are suitable for solving NP-hard problem. Nature inspired algorithms use inexact approaches to solve computationally hard problems, they include different approaches like genetic algorithms (GAs), particle swarm optimization(PSO), Differential Evolution (DE). GA is gaining a lot of attention as a new soft computing technique inspired by nature, in this research the application of GA for solving the problem of estimating lightness of the skin for cancer therapy is investigated from both aspects of error rate and time (Yadav et al., 2017; Duan at al., 2017). Similarly, DE is one of the stochastic, population-based optimization algorithm. DE optimizes a problem

by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae (Hadi et al., 2017). PSO is one of the swarm Intelligence techniques that simulate the behavior of bird flocking. It is a population-based optimization tool, which could be implemented and applied easily to solve various function optimization problems (Gong et al., 2017).

For instance, one such process involved dividing the simulation into many independent sub processes, in parallel each of which was run on a various processor. An issue with this approach is the required for a huge, shared network cluster for treatment planning, which tends to returns less accuracy, and use more time compared to an existing method In order to overcome the problem of PDT, the main objective of this work is to reduce error rate and speed up an MC simulation (Pasciak and Ford, 2008) based on the widely basic Charged System Search Algorithm, called Monte Carlo for Wavelet based Genetic Algorithm Search (WGAS). It has been wide variety of applications in solving numerous optimization problems in civil engineering area and can apply for digital signal processing application (Charles, 1992). Therefore, through different tissue layers it imitates the propagation of photons to c. The main objective of this proposed work minimizing the error in the context of PDT treatment planning.

## Materials and Methods

### Charged Genetic Algorithm Search (CGAS) – an Overview

Charged Genetic Search Algorithm Search is an evolutionary based metaheuristic algorithm (Goldberg, 2009). It is implemented with the basic principle of the Gauss and Coulomb laws and the prevailing laws of motion of the Newtonian mechanics (Fanti et al., 2006). This evolutionary algorithm is a multi-swarm based approach, where each swarm is called as the Charged Swarm (CS). Based on general theory of physics, all swarm are considered as charged sphere with radius and possessing uniform volume charge density which results in electric force on the other individual swarm.

The movement of CSs and their change in position is carried out based on the force magnitude computed (Van den Bergh and Engelbrecht, 2004). Distance between the CSs is proportional to that the force magnitude for a particular CS located inside the sphere, whereas for that of the CS located outside the sphere it is found to be inversely proportional to the square of the separation distance between the particles. Thus the new location or position of CP is computed based on the resultant forces or acceleration and the motion laws.

### Procedure of Wavelet with GAS (WGAS Algorithm)

In case of CGAS algorithm, the charged swarm will move towards the search space and perform diversification between the evaluated fitness values. Looking into the equations (1) of position and velocity of GAS algorithm, there exists a scaling factor ‘ $\alpha$ ’ and it is where the wavelet function is been introduced.

$$\alpha = \frac{1}{\sqrt{a}} e^{-\frac{(\frac{x}{a})^2}{2}} \cos\left(5\left(\frac{x}{a}\right)\right) \quad (1)$$

where a is the dilation or scaling parameter, and translation or shifting operator b becomes equal to zero. Equation (1) depicts the wavelet principle. This is the part where WGAS algorithm is different from that of the original GAS algorithm. Otherwise, all the steps for GAS algorithm and proposed WGAS algorithm are the same.

Therefore to improve the searching performance in the fine tuning stage, this property will be attained via in updation operation. The mother wavelet function is contained all over 97% of the total energy of in the interval [-2.5, 2.5] for the function defined in equation (1), x is generated randomly from . The dilation parameter a can be set to vary with the value of n/N to saturate the fine tuning needs, where N is the maximum number of iterations and n is the current iteration number. a and n/N may be written as given in the following equation to govern in monotonic increasing function.

$$a = e^{-h(g_i) \times \left(1 - \frac{n}{N}\right)^{\xi_{\text{com}}}} + h(g_i) \quad (2)$$

where  $a_{\text{max}}$  is the upper limit of the parameter a and  $h$  is the shape parameter of the monotonic increasing function. The range of a is thus between 1 and  $a_{\text{max}}$ . To perform effective diversification search stages and fine tuning during the local search or intensification stage near the end of the maximum epochs (Paradalos et al., 2001). The magnitude of the parameter  $\xi_{\text{com}}$  decreases as a increases toward  $a_{\text{max}}$  with the increase in iteration cycles. Therefore, a stability between the diversification of new regions and the intensification of the already sampled regions in the search space is expected in WGAS Algorithm and which is been achieved with the introduction of wavelets for updation process.

## Results

The proposed WGAS algorithm is implemented for the computing the optimal FIR filter coefficients for LP, HP, BP and BS filter types to accurate computation of light dose distribution. The normalized filter coefficients for carrying out the simulation process and various parameters considered for proposed WGAS algorithm is as given in Table 1.

The experiment and analysis for determining the optimal FIR filter coefficients is carried out in MATLAB R2012a environment and run in a PC with Intel core i3 processor with 2.7 GHz speed and 16GB RAM with 64 bit operating system. Table 2 shows the optimal FIR filter coefficients of LP, HP, BP and BS filters tuned using the proposed WGAS algorithm and is compared with that of the other evolutionary algorithms used for computing the coefficients as taken from the literature studies (Liu and Lampinen (2009); Kennedy and Eberhart,1995; Storn and Price, 1997).

Table 3 depicts the Fitness Error values for all types of

Table 1. Parameters for Proposed WGAS Algorithm

Parameters	Values
No. of Population	50
Crossover	0.9
Mutation	0.001
Maximum Iteration	50
Filter Coefficients Limits	-2 to +2
$C_{wm}$	2
$g_1$	10000

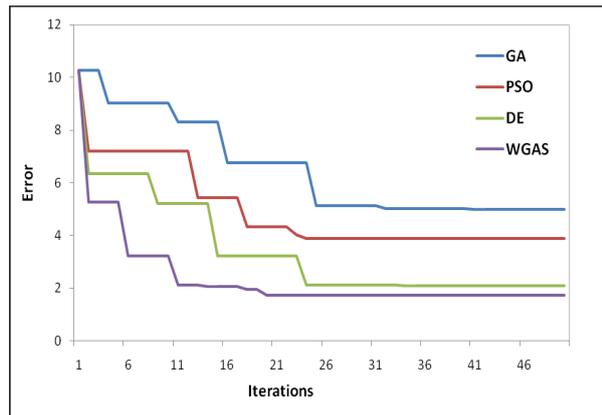


Figure 1. Convergence Plot of FIR High Pass Filter for 50 Iterations vs Error

FIR filters with iteration count using WGAS algorithm. The response error values of the other population based methods such as GA, PSO and DE are obtained (Yadav et al, 2017; Gong et al., 2017; Hadi et al., 2017). It is easy to see that WGAS is better than other existing evolutionary approaches on most of FIR types. For those simple types such as High Pass Filter and Band Stop Filter, the two FIR can obtain the global optimal value in minimum number of iterations. Thus the proposed WGAS algorithm outperforms to compute optimal filter coefficients with a faster convergence rate in comparison with the proposed algorithms.

Figure 1 depicts for FIR Low Pass Filter of order

Table 2. Optimal FIR Filter Coefficients for Order 20 Employing Proposed WGAS Algorithm

h(N)	Optimal FIR LP filter coefficients	Optimal FIR HP filter coefficients	Optimal FIR BP filter coefficients	Optimal FIR BS filter coefficients
h(1) =h(21)	0.05231	0.61249	0.40124	0.01445
h(2) =h(20)	0.05122	0.00123	0.00231	0.00054
h(3) =h(19)	0.00216	0.00319	0.00389	0.07765
h(4) =h(18)	-0.08766	0.05415	0.00453	0.07761
h(5) =h(17)	-0.00208	0.00054	0.06512	-0.03982
h(6) =h(16)	0.05412	-0.06154	0.04319	-0.07001
h(7) =h(15)	0.006109	0.00459	0.26573	-0.00564
h(8) =h(14)	-0.1283	0.20017	-0.006189	-0.07327
h(9) =h(13)	0.00418	-0.00514	-0.30561	0.48044
h(10)=h(12)	0.40012	-0.45428	0.007001	0.069032
h(11)	0.55109	0.65559	0.44395	0.58791

Table 3. Fitness Error Values for All Types of FIR Filters with Iteration Count

Filter Type	Considered Algorithms for comparison	Iteration cycles	Fitness Error Values
FIR Low Pass Filter of order 20	GA	42	5.1927
	PSO	24	4.0183
	DE	39	1.9927
	Proposed WGAS	28	1.7162
FIR High Pass Filter of order 20	GA	38	4.2127
	PSO	46	3.9321
	DE	43	2.0045
	Proposed WGAS	19	1.7369
FIR Band Pass Filter of order 20	GA	39	4.8854
	PSO	42	4.0009
	DE	46	2.9284
	Proposed WGAS	23	1.4725
FIR Band Stop Filter of order 20	GA	39	4.9119
	PSO	45	3.9677
	DE	42	3.6128
	Proposed WGAS	18	1.6436

20 with 50 iterations. It is indicated that the proposed evolutionary wavelet based GAS converges to the high accurate value quicker than that of the other methods. Moreover, WGAS based MC maintains balanced intensifications and diversifications in the entire solution of the search space. Thus for all the filter types, the proposed WGAS converges with minimal execution times to the least minimum error fitness values.

## Discussion

Error rate is an important metric to compare computational efficiency between the WGAS and the other population based meta-heuristic approaches like PSO, GA and DE. At first, without wavelet GA optimized hardware showed an increase in error of 36% in the simulation output when the number of photon packets fixed. However GA has move to determine the source of error, empirical tests on accuracy were done on the various fixed-point conversions and the random number generator. Due to local convergence of PSO depicted an increase error rate 20%. Finally, compared with proposed method, DE algorithm gives an increase error rate of 6%. When multi-objective is used the result may fall into approximation.

For example, consider filter type FIR Low Pass Filter of order 20, the proposed WGAS fitness value is 1.7162. Due to balanced intensification and diversification of WGAS, it returns minimum error for 28th iterations itself. Whereas GA, PSO and DE error rate are 5.1927, 4.0183, 1.9927 respectively. WGAS reached a better solution than genetic algorithms and and swarm intelligence approach PSO although the result acquired by differential evolution algorithm is the nearer as WGAS. It has a very better merit that it does not need exhaustive parameter tuning like Particle Swarm Optimization and GA.

PID treatment planning enables real time treatment planning based on the most recent images of the clinical target volume, taking into account the changing tissue optical properties as the treatment progresses. In this paper, a Wavelet GAS algorithm has been proposed and implemented to improve accurate solution for light dose distribution, but have low computation time that prevents them from being used in treatment planning. Fitness error of proposed method was investigated with various optimization methods like GA, PSO and DE. Thus, the proposed WGAS algorithm is validated to design practical digital FIR filter. It also acts as a global optimizer for obtaining the optimal filter coefficients for digital signal processing applications.

The considerable performance gain furnished by the WGAS approach allows PDT treatment planning in heterogeneous. It involves for spatially complex tissues using more sophisticated MC-based models. The experimental results are more accurate and scalable in nature allowing better solutions in comparison with that of the existing benchmark evolutionary techniques. However, the proposed WGAS approach is a stochastic algorithm. In general, it can have difficulty obeying quality constraints as well as it is sensitive for initial population used.

#### Statement conflict of Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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