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A Novel Discrete Particle Swarm Optimization Algorithm for Estimating Dielectric Constants of Tissue

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Abstract— **Global optimization algorithms basically create a set of solutions, classify them, and then search for the best answer, iteratively. In this paper, a new discrete particle swarm optimization algorithm is proposed to estimate the permittivity arrangements of lossy multilayer structures, which represent body tissue models. Microwave imaging (AMI) is the modality in which the proposed algorithm is used for reconstructing the image. The main objective of this article is to depict the flexibility of PSO-based methods in handling complex problems expeditiously and successfully. Our new algorithm improves the estimation time by 85% as compared to our previous proposed one. Here, the impact of various parameters, namely, the AMI frequency, the immersion medium, the number of agents, the smoothing coefficient, and the maximum velocity, on the estimation performance are studied in terms of the maximum estimation error. It is demonstrated that by choosing the parameters correctly, one can achieve estimation results with a maximum error less that 10% in only 0.1 minute.**

I. INTRODUCTION

Active microwave imaging (AMI) has been recently utilized in a variety of demanding applications. Basically, in AMI, the scattered/transmitted fields from/through an inhomogeneous structure at microwave frequency band are collected and analyzed in order to define the composition of the object under test. The dielectric constants of the contents are often calculated as the indicators of the material type. Among all applications introduced in the literature, those assisting biomedical diagnostics have recently received a lot of attention. A comprehensive review of these types of applications can be found in [1]-[3]. In these studies, AMI is used to create an image of the human body by highlighting the contrast between dielectric constants of different tissues. AMI techniques deal with inverse electromagnetic problems, for which a variety of algorithms have been proposed and studied in the literature [3]. It is quite evident that the algorithm needs to be relatively fast and reasonably accurate for biomedical diagnostics. However, such complex inverse problems potentially end up with non-unique results. For that reason, global optimization algorithms prove to be more appropriate computational techniques for such scenarios as compared to the analytical optimization methods. There are some articles in the literature which use evolutionary algorithms for similar problems (see [4] and [5]). When using evolutionary algorithms, the main challenge is to analyze and classify the results obtained by a large number of agents, at each iteration, and to lead the algorithm in the correct path, accordingly, toward achieving the best estimation, which is the correct composition of the tissue under the test. A burden in this study is the penetration depth, which is restricted by the high absorption rate of the electromagnetic energy by body tissue at frequencies of interest to the AMI studies. Yet, some parts of human body, such as breast, are suitable candidates for AMI. It should be noted that since microwave radiation is non-ionizing and microwave technology is relatively cheap and reliable, AMI is a promising modality for mass-screening in the case of breast cancer where routine checkups are required.

In our previous work, [6], we demonstrated how PSO algorithms can be successfully used as search and detection algorithms in a complex AMI problem. There, we used two proposed versions of PSO, based on complex number and discrete PSO, and estimated the arrangements of complex dielectric constants in a lossy multilayer material which was actually a model for the breast tissue. Two main factors that made our study distinct from the other ones available in the literature were introducing new versions of PSO algorithm and having a human body model with exact loss factors introduced in the measurement studies, see [7]. These loss factors have generally been ignored or over simplified in order to decrease the complexity of the problem [8]-[9].

Here, we propose an optimized version of discrete PSO (DPSO) with comprehensive study of the algorithm accuracy under different conditions. The new algorithm achieves similar results with 85% improvement in the computation time. In addition, various conditions are studied, each in a hundred runs in order to guarantee reliability of presented conclusions. The maximum error percentages of the complex dielectric constants, both real and imaginary parts, are used as the figures of merit. What is meant here by the ”maximum error” is the maximum deviation of the estimated dielectric constants of the layers from their corresponding actual values in percentage. The effect of different AMI and PSO parameters are studied.

II. PROBLEM SCOPE AND ESTIMATION ALGORITHM

The proposed DPSO algorithm in this paper finds the tissue-types and their corresponding dielectric constants in a hierarchical manner (see Fig. 1). The makeup of each tissue layer is first selected from a set of six possible tissue groups, namely, (t1: skin), (t2: adipose dominant tissue), (t3: 30%-80% fatty tissue), (t4: glandular tissue), (t5: blood) and (t6: malignant tissue), see [7]. For the sake of conciseness, the tissue-types will be called with their t-numbers throughout

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this paper. These six groups are, in fact, the tissue-types one can expect to find inside the breast. After tissue-type selection, the best complex values of the dielectric constants are found inside the variation spans assigned to those tissues in the literature,[10]. In other words, here, the inherent variations of the dielectric constants of the tissues are also taken into account. These variations are created by differences which exist either between different people or, in a single person, under different conditions. We have considered 10% as the error threshold shown in Fig. 1. It means, if all the estimated dielectric constants have an error of lower than 10%, then the second optimization cycle is activated. It is noteworthy that the threshold of 10% does not address a perfect estimation, however it is acceptable in AMI, since the chance of detecting the tissue-type incorrectly is very low at this threshold. In addition, 10% variation can even happen due to inherent inaccuracies in this process.

It is shown in the literature that the popular PSO velocity function (equation 9 in [11]) can be used for binary PSO, as well. The only requirement is a mapping function which maps the real values to zeros and ones (see equation 12 in [11]). Likewise, for DPSO, a similar mapping function is introduced here to address the six required levels. The mapping function is shown in 1.

$$S = 0.5 + NT/(1 + exp(-v \times sc)) \tag{1}$$

where sc is the smoothing coefficient and NT is the number of tissue types which is equal to six for the breast tissue considered in this paper. v is the velocity and is a real number. Fig. 2 shows the mapping function using different smoothing coefficients. It should be noted that, in order to have a correct mapping, the maximum allowed velocity should be selected with respect to sc. To further illustrate, in Fig. 2, any velocity value mapped inside $[a-0.5, a+0.5)$ is interpreted as a. Equation 2 shows the fitness function that

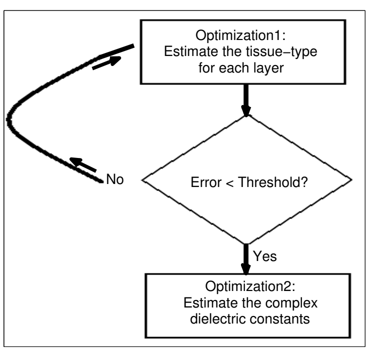

Fig. 1. The two considered optimization procedures.

is minimized by DPSO. R and T depict the reflectance and transmittance coefficients.

$$\begin{aligned} f \quad = \quad & \sum\{||R_{actual}| - |R_{estimated}|| + \\ & |\arg(R_{actual}) - \arg(R_{estimated})| + \\ & ||T_{actual}| - |T_{estimated}|| + \\ & |\arg(T_{actual}) - \arg(T_{estimated})|\}; \end{aligned} \tag{2}$$

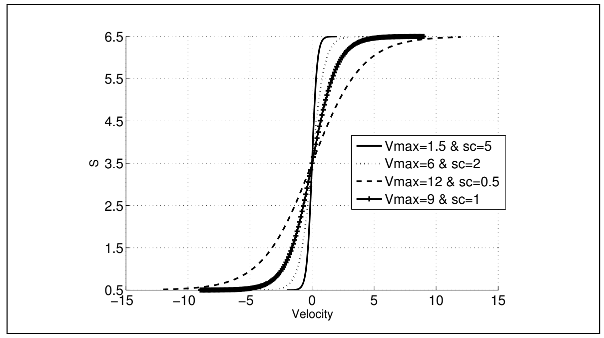

Fig. 2. Mapping function with different smoothing coefficients.

where arg() denotes the phase of the enclosed complex number. Assuming a narrow beam radiation, the normal incidence of plane wave to multilayer structure is considered [12]. Here, both magnitude and phase errors are taken into account in 2, as such quantities bear distinct information relevant to the optimization process [12]. Also, an immersion medium is considered to surround the tissue, as it is recommended in many other research articles for AMI improvement [2]-[3].

The default immersion medium is assumed to be similar in properties to the fatty tissue (t2). Two types of controlling parameters are involved in this problem: (1) AMI parameters and (2) DPSO parameters. AMI parameters are the immersion medium, tissue thickness and the radiation frequency. The controlling gears of DPSO are the maximum allowed velocity ($Vmax$), which is related to the smoothing coefficient in the mapping function, and the number of agents. The effects of these parameters are studied in the next section in terms of the estimation error in 100 independent runs per analysis. Each run is limited to 1000 iterations for the first optimization operation shown in Fig. 1 and 100 iterations for the second one.These numbers were chosen by trial and error in order to optimize both the final error and the computation time.

To be able to compare the results with those presented in [6], the tissue is modeled as a 5-layer structure (t1, t2, t4, t2, t1) for which it is shown in the next section that 40-agent swarm ($m = 40$) is fairly strong to gain an accuracy better than 10%. Reviewing the model, one can easily recognize that this is a model of normal breast tissue. The thicknesses of the tissues are t1:2mm, t2:15mm, and t4:10mm. The total thickness is 4.4cm, which represents a good model for the breast tissue when the tissue is squeezed for AMI measurement. Although other frequencies are also studied, the reference frequency in this paper is 1GHz, which has been proved to be appropriate for AMI [6].

III. Parameter Variation Study

A. AMI Parameters

As the first AMI parameter, immersion medium is studied. This medium acts as matching interface for the fields to enter the body tissue with lower reflections. Fig. 3 shows the effect of using different types of immersion media on the detection error in 100 runs. It should be noted that, unlike other studies associated with AMI immersion medium, here, the impact of this intermediate medium on the optimization trend of the search algorithm is underscored. The dielectric constants of air, water and fat at 1GHz are assumed to be 1, $78.2-3.796j$ and $4.79-0.8j$, respectively. As it is evident in Fig. 3, the probability of achieving a final estimation with error higher than 10% increases to 6% in the case of water. It is interesting that this increase in error happens for imaginary part of the dielectric constant which has lower significance in defining the tissue type. However, the mean error percentage for all three cases remains between 7% and 9%. It is worth mentioning that for the case of fat, the maximum required iteration number is 191, which is almost 20% of the maximum iteration number of 1000 (see table I). This study simply confirms that oily and fatty substances are preferred for AMI.

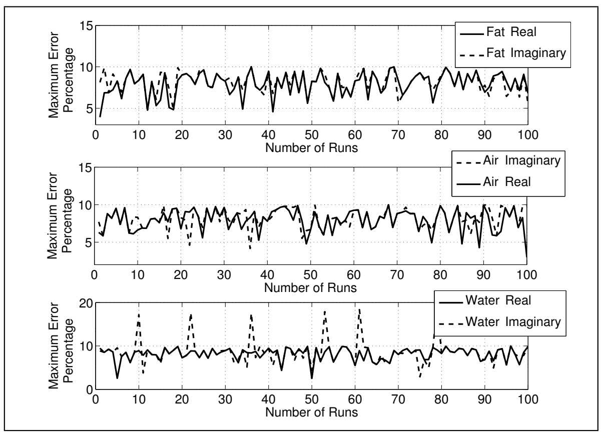

Fig. 3. The effect of immersion medium on detection error for a 44mm-thick tissue at 1 GHz. *Vmax*, *sc* and *m* are considered to be 1.5, 5 and 40, respectively.

Fig. 4 shows the estimation error at two other frequencies, 500 MHz, and 5 GHz. 5 GHz case, apparently, has the highest probability of error while 1 GHz (Fig. 3) has the lowest probability of error. It is interesting that the standard deviation of the results achieved from 5 GHz study is more than four times that of 1 GHz study. The mean error percentages, however, for all the cases remain between 7.5% and 12% (see table I). Although 500 MHz radiation has higher chance of penetration than its 1 GHz counerpart, the relative thicknesses of the tissue-layers with respect to the wavelength should also be considered.

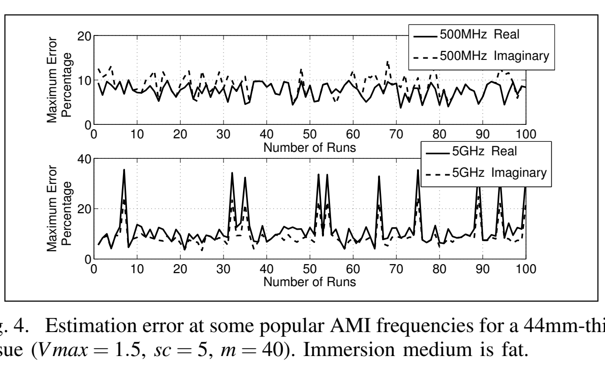

Fig. 4. Estimation error at some popular AMI frequencies for a 44mm-thick tissue ($Vmax = 1.5$, $sc = 5$, $m = 40$). Immersion medium is fat.

In practice, the tissue thickness is defined by the person's body style (fat, skinny, etc.). Here, we repeat the study for another case in which the thicknesses of the t2 and t4 tissues are increased by 5 mm. The total tissue thickness is 59 mm in this case. As shown in Fig. 5, the probability of achieving an estimation with an error level higher than 10% increases to 3% when considering fat as the immersion medium. Nonetheless, the mean error percentage for all the cases stays in the range of 7.5-8.5%.

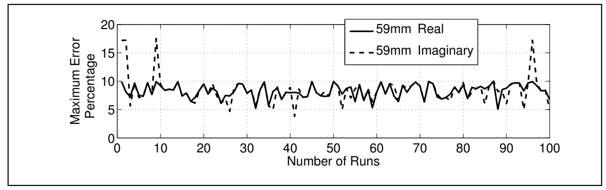

Fig. 5. The error for thicker tissue($f = 1$GHz, $Vmax = 1.5$, $sc = 5$, $m = 40$).

B. DPSO parameters

AMI parameters studied in previous subsection are very important; however, they are not fully under the control of the AMI operator. Optimization algorithm, on the other hand, can be controlled with less limitations. In this subsection, the impacts of some of the optimization parameters on the estimation process are studied.

It should be noted that, correctly mapping the real velocity values to discrete values is quite challenging. The first step is to define the smoothing coefficient of the mapping function. By decreasing *sc*, introduced in 1, the probability of achieving errors higher than 10% increases. Further increasing of *sc* above 5 will not result in any further improvement either. Therefore, here we demonstrate our results mostly considering $sc = 5$. The second issue is the maximum velocity. In discrete versions of PSO, due to intrinsic limitations imposed by mapping function, $Vmax$ does not have the same direct impact on the performance as it has in the real number PSO case. Reviewing Fig. 2, one can simply conclude that $Vmax$ should be selected with respect to *sc*, not only to cover all six levels, but also to preserve a smooth variation. As shown in Fig. 6 and Fig. 3, the average errors for $sc = 0.5$, 1, 2, 5 and 10 are 8.5, 8.1, 7.8, 8.1 and 7.7, respectively. Lower $Vmax$ offers higher estimation accuracy; however, it also increases the required number of iterations in order to converge. On the other hand, higher velocities decrease the chance of finding the solution. $sc = 5$ and $Vmax = 1.5$ are the best parameter set for keeping the error below 10% in all 100 runs for this problem.

Finally, the number of agents is studied. It is shown in the literature([13]) that, although having large number of agents improves the search activity, it also increases the optimization cost in terms of computation resources and optimization length. Therefore, it is always desired to find an optimum agent-number. As it is shown in Fig. 7, lowering the number of agents from 40 to 30 increases both the probability of achieving higher errors than the desired 10% and the average maximum error. Furthermore, increasing the

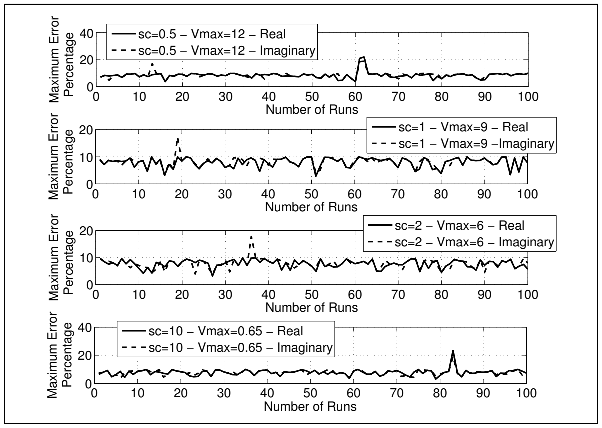

Fig. 6. Estimation error for a 44mm-thick tissue at 1GHz when assuming different maximum velocities and smoothing coefficients. 40 agents are considered.

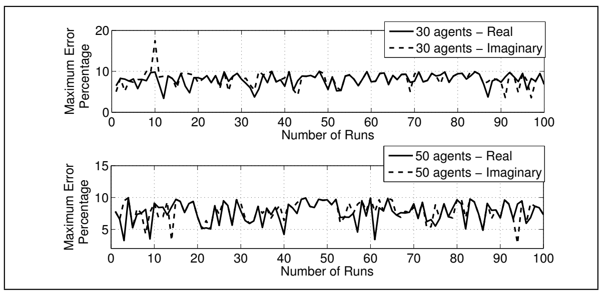

Fig. 7. Estimation error for a 44mm-thick tissue at 1GHz when assuming different number of agents. $Vmax$ is 1.5 and sc is 5

number of agents to 50 decreases the average error from 8% in the case of 40 agents to 7.8%, which is not a significant improvement.

TABLE I

OPTIMIZATION LENGTH COMPARISON

Medium	F(GHz)	m^1	max($iter^2$)	mean(iter)	P^3(high error)
air	1	40	33	222	0
water	1	40	1000	158	6
fat	1	40	191	50	0
fat	5	40	1000	454	40
fat	0.5	40	1000	370	26
fat	1	30	1000	93	0
fat	1	50	190	47	0

[1] Number of agents
[2] Required number of iterations for lower than 10% error
[3] Probability of achieving higher than 10% error

Table I summarizes the optimization length for some of the cases studied in this paper. Comparing these results with those shown in [6], one can simply conclude that the new version of DPSO, introduced in this paper, has significantly enhanced the detection performance by decreasing the estimation time by 85%.

IV. CONCLUSION

In this paper a new version of discrete particle swarm optimization algorithm was introduced and utilized to estimate the permittivity arrangement of human breast tissue model. Active microwave imaging was considered at frequencies of 500 MHz, 1 GHz and 5 GHz. The impact of different parameters, namely, frequency, immersion medium, tissue thickness, number of agents, smoothing coefficient, and maximum velocity on the estimation performance were studied in terms of the maximum estimation error. It was demonstrated that by choosing the parameters correctly, one can achieve fast estimation results with a maximum error less that 10% in less than 200 iterations. This accuracy is sufficiently high for AMI applications. Using standard 2.83 GHz PC, a set of 100 runs requires almost 10 minutes of computational time for the introduced 5-layer model using 40 agents, smoothing coefficient of 5, and maximum velocity of 1.5. The computation time is 0.1 minute for each run in average which is 85% less than that reported with the other version of DPSO.

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