Parameter optimization of temperature field in RF-capacitive hyperthermia*

WAN Baikun (万柏坤)[1**], ZHU Xin (朱 欣)[1], CHENG Xiaoman (程晓曼)[2], ZHANG Lixin (张力新)[1], LIN Shiyin (林世寅)[3] and WANG Wei (王 伟)[3]

1. Department of Biomedical Engineering and Science Instrument, Tianjin University, Tianjin 300072, China
2. Department of Opto-electronic Information and Electronic Engineering, Tianjin Institute of Technology, Tianjin 300191, China
3. Division of Radio-Physics, Tianjin Cancer Institute, Tianjin 300060, China

Received December 25, 2000; revised February 19, 2001

Abstract To realize a certain target temperature distribution in tumor tissues and avoid over-heating in normal tissues in radio frequency (RF)-capacitive hyperthermia, an objective function and some weight coefficients are introduced. Then using the 2-D finite element method, the electromagnetic and bio-heat transfer equations are solved, and using the genetic algorithm the heating configurations are recursively modified to minimize the objective function. Finally an optimum solution of the expected heating field distribution in hyperthermia is achieved. And with a human heterogeneous tissue model extracted from X-ray CT images, satisfactory optimization results are obtained in the simulations on a biplate RF-capacitive hyperthermia device. This optimization technique for controlling the body temperature field has shown scientific importance and practical values in the research of hyperthermia.

Keywords: radio frequency-capacitive, hyperthermia, optimum solution, heating physical parameters, finite element method, genetic algorithms.

One of the most important and difficult problems of hyperthermia is how to control the distribution of body temperature, i. e. how to heat target tumor tissues to an effective oncology temperature (43 ~ 45℃) without hurting normal tissues (below 40℃)[1]. In the present clinical implementation, the adjustment of the physical configuration (the applicators' powers, sizes, locations, potentials, phases, etc.) of a hyperthermic device depends heavily on the experiences of physical therapists. As a result, the ultimate therapy efficiency is greatly reduced by subjective factors and expected heating temperature distribution is rarely reached[2]. Therefore, it is quite important to forecast the distribution of body temperature field under a possible heating physical configuration before selecting physical parameters and establishing clinical therapy plan. Due to the extreme difficulty in noninvasive temperature measurement, a compromise solution that optimizes the biological temperature field by numerical simulations is considered to have a bright practical future[3]. Due to the heterogeneity and anisotropy of human tissues, the determination of their temperature field is arduous, not to mention the optimization. To date, most hyperthermia researches were concentrated on the prognostication of the temperature distribution with given specific physical parameters[4], whereas the optimization of such parame-

* Project supported by the National Natural Science Foundation of China (Grant No. 39270218, 39870237)

** E-mail: bkwan@bj.homeway.com.cn

ters was rarely studied. In this paper, an optimization method is put forward to find the optimum heating physical parameters corresponding to the expected temperature field in hyperthermia. Starting with the introduction of an objective function, namely the difference between the calculated temperature distribution and the expected one, then using an optimization algorithm to recursively modify the heating conditions and to minimize the objective function, this method enables us to get an optimum heating configuration of the expected heating field distribution in hyperthermia. A 2-D finite element method (FEM) is applied to determining the temperature distribution[5], and the genetic algorithms are selected to realize the iterative optimization process instead of the traditional conjugation gradient algorithm[6]. With a human heterogeneous tissue model extracted from X-ray CT images, satisfactory optimization results are obtained in the simulations on a 2-capactive RF-hyperthermia device. The simulation results on the phantoms containing only a single deep-seated tumor, a shallow-seated tumor and both deep-and shallow-seated tumors are discussed separately.

1 Computation of body temperature distribution

RF-capacitive hyperthermia is a regular therapy method used in clinics. To evaluate the heating effects of RF-capacitive applicators, the coupling of electromagnetic and temperature fields should be considered. The former can be analyzed by solving the Laplace equation to attain the electric field distribution, while the latter can be analyzed by solving the bio-heat transfer equation to get the body temperature distribution induced by the heating of the electric field. As the wavelength of the RF radioactivity ($\approx$30m) is much greater than the depth of human body ($\approx$0.3m), the quasi-static electric field approximation[4] can be presumed and the electric scalar potential ϕ can be governed by the following Laplace equation:

$$\nabla(-\varepsilon\nabla\phi) = 0, \tag{1}$$

where ε is the permittivity varying spatially due to the heterogeneity of tissues. The electric field $\boldsymbol{E}$ can be obtained from the distribution of electric scalar potential ϕ,

$$\boldsymbol{E} = -\nabla\phi. \tag{2}$$

The RF currents in the biological tissues resulting from electric field $\boldsymbol{E}$ can produce ohmic heating effect. The yielded heat Q_s or specific absorption rate (SAR) can be calculated as follows:

$$Q_s = 0.5\sigma_t |\boldsymbol{E}|^2. \tag{3}$$

According to the law of conversation of energy, the temperature distribution in the heating domain tissues can be obtained by the Pennes' bio-heat transfer equation[7]:

$$\rho_t C_t \frac{\partial T}{\partial t} - \nabla(K_t \nabla T) = Q_t + Q_s - Q_b, \tag{4}$$

where σ_t, ρ_t, C_t, K_t are electric conductivity, density, specific heat in constant pressure, and thermal conductivity, respectively, Q_t represents the physiological thermal effect, Q_s(SAR) is the heat produced by the electric field, and Q_b the cooling effect of the blood perfusion. Generally speaking, Q_t can be ignored as compared to Q_s and Q_b[5]. Parameter Q_b is described by the following equa-

tion:

$$Q_b = (F_b)_t(\rho_b C_b)(T - T_b), \tag{5}$$

where $(F_b)_t$ is the blood perfusion rate in the tissue, ρ_b and Q_b are density and specific heat with constant pressure of blood, T_b is the temperature of blood (defined constantly at 37℃). It is supposed in this paper that $(F_b)_t$ does not vary independently of temperature (the case where $(F_b)_t$ varies with temperature will be discussed in a subsequent paper).

Table 1 The electric and thermal parameters of biological tissues

Tissue	ε_r	σ_t/s m^{-1}	κ_t/W m^{-1} K^{-1}	ρ_t/kg m^{-3}	C_t/J kg^{-1} K	$(F_b)_t$/m^3 kg^{-1}s^{-1}
Blood	118.0	1.100	0.000	1.06×10^3	$3.96*10^3$	—
Bone	7.3	0.028	0.436	1.79×10^3	1.30×10^3	4.20×10^{-7}
Fat	20.0	0.047	0.220	0.90×10^3	2.30×10^3	5.00×10^{-7}
Faeces	113.0	0.600	0.600	1.00×10^3	3.90×10^3	0.00
Marrow	200.0	0.650	0.515	1.10×10^3	3.96×10^3	7.50×10^{-6}
Muscle	113.0	0.610	0.600	1.02×10^3	3.50×10^3	8.30×10^{-6}
Tumor(surf.)	60.0	0.800	0.570	1.04×10^3	3.90×10^3	1.67×10^{-6}
Tumor(deep)	60.0	0.800	0.570	1.04×10^3	3.90×10^3	5.00×10^{-7}

Equations (1) ~ (5) are solved by 2-D-FEM. The hyperthermia device is a biplate RF-capacitive hyperthermia system. In Table 1 are listed the electric and thermal parameters[1] used in the simulations.

2 Optimization analysis

According to the hyperthermia theory and clinical experiences, the target temperature distribution in tumor tissues was set between 43 and 45℃, and that in normal tissues between 30 and 40℃. The heating physical configuration includes the sizes, locations, and heating powers of the two electric plates. The boundary electric scalar potentials ϕ, $\{\phi\} = \{\phi_1, \phi_2, \cdots \phi_i, \cdots, \phi_m\}$ (Dirichlet conditions), were determined by the sizes and locations of electric planes, where ϕ_i was the potential of ith boundary node of finite element model just under the electric planes. While the boundary conditions of other boundary nodes were described by Neumann conditions: $-\frac{\partial \phi}{\partial n} = 0$. Moreover, between the skin and applicators there existed water boluses to disperse the extra heat produced by the marginal electric field of the RF-capacitive plates. The water bolus kept a stable cooling temperature(15℃) through water circulation.

It is expected that, by optimizing the parameters of the heating electric plates due to the pre-defined target temperature distribution, the calculated temperature distribution can approach it as closely as possible. Therefore, the objective function J of this optimization problem is defined in the following way:

$$J = \int_\Omega \lambda F_T[T(\phi)]\mathrm{d}\Omega, \tag{6}$$

where ϕ is the boundary potential distribution to be optimized, Ω the domain of the finite element model, λ the respective weigh coefficient of different sub-domains in the objective function, and F_T the temperature objective function with F_{T1} for tumor tissue and F_{T2} for normal tissues.

$$F_{T1}(T) = \begin{cases} T - 45 (T > 45℃) \\ 0 (43℃ \leqslant T \leqslant 45)℃ \\ 43 - T (T < 43℃) \end{cases} \tag{7}$$

$$F_{T2}(T) = \begin{cases} T - 40 (T > 40℃) \\ 0 (40℃ \leqslant T \leqslant 30)℃ \\ 30 - T (T < 30℃) \end{cases} \tag{8}$$

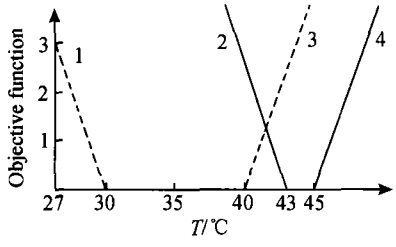


Fig. 1 Objective functions for tumor tissues $F_{T1}(T)$ (lines 2 and 4) and normal tissues $F_{T2}(T)$ (dashed lines 1 and 3).

Fig. (1) shows that $F_{T1} = 0$ when the temperatures in tumor tissues are 43 ~ 45℃; $F_{T2} = 0$ when the temperatures in normal tissues are 30 ~ 40℃.

For the convenience of numerical computation, the F_T integration in Eq. (6) is expressed as its discrete form:

$$\int_{\Omega} F_T[T(\phi)]d\Omega = \lambda_1 \sum_{i=1}^{N_1} F_{T1}[T_i(\phi)] + \lambda_2 \sum_{j=1}^{N_2} F_{T2}[T_j(\phi)], \tag{9}$$

where N_1 is the number of the nodes corresponding to tumor tissues in the model, N_2 is that corresponding to normal tissues, λ_1 and λ_2 are the weight coefficients for the objective functions in the integral domains of tumor and normal tissues, respectively. By applying genetic algorithms, the boundary potential distribution was modified recursively until the variation of the fitness function value between neighboring generations was less than a specific threshold. And as the tournament selection operator was selected in this research, the fitness function was just the same as the objective function.

2.1 Genetic algorithms

Genetic algorithms are a sort of parameter search procedures based upon the mechanics of natural genetics[8]. This technique has gained in popularity recently as a powerful and robust optimization tool for a variety of complex multi-object problems in engineering, science, economics, and so on. By employing selection, crossover, and mutation operators, a global or near-global optimization result can be achieved by genetic algorithms through several generations' evolution. In this paper, a small population method——micro genetic algorithm (μGA) with some very simple genetic parameters[9]——is utilized for the optimization solution search. It is shown that with μGA the near-optimal region is reached earlier than that with the simple GA. And μGA has the merits in solving non-stationary, multi-model, maximum, or minimum optimization problems. In μGA, the population size is fixed at five. To avoid the insufficient information processing and early convergence to non-optimal re-

sults caused by small population, some new strings are brought at a regular interval into the population and the best string of the present generation is carried to the next generation to guarantee that the information about good schema is not lost. The mutation rate is kept at zero, as it is clear that enough diversity is introduced after every generation convergence through new populations of strings. The crossover rate can be set between 0.7 and 0.9.

A step by step procedure for the μGA implementation is presented below:

(i) select a population of size 5 to form the initial generation;

(ii) evaluate fitness and determine the best string. Label it as string 5 and carry it to the next generation (elitist strategy) so as to guarantee that the information about good schema is kept;

(iii) choose the remaining strings for reproduction (the best string also competes for a copy in the reproduction) based on the tournament selection strategy;

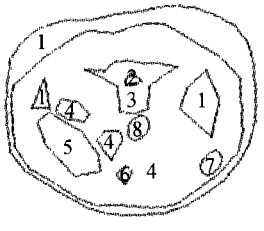
(iv) apply crossover among the selected strings with a certain probability. The mutation procedure is unnecessary;

(v) check nominal convergence, if not converged, go to step (ii);

(vi) if the number of recursive generations is less than the permitted maximum number, string 5 and the other 4 newly chosen strings are used to form the next generation and go to step (ii).

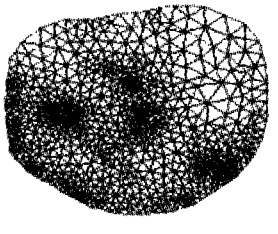
3 Simulations

To approach the clinical reality of hyperthermia more accurately, a simplified human heterogeneous tissue model extracted from X-ray CT image is used in the simulations for the optimization computation. Fig. 2 (a) shows the slice structure of heating torso, where there is a shallow-seated tumor, or a deep-seated one, or both of them. Fig. 2(b) shows the finite element model with 1555 elements and 826 nodes (for the model with two tumors). Both initial and blood temperatures in the human body were set at 37℃, and the initial locations, sizes, and potentials of electric plates were randomly selected.



(a)

1. Fat
2. Marrow
3. Bone
4. Muscle
5. Faeces
6. Blood
7. Tumor (shall ow)
8. Tumor (deep)



(b)

Fig. 2 Slice structure of heating torso (a) and finite element model (b).

4 Results and discussions

Figure 3 shows the optimization hyperthermia results in the case of shallow-seated tumor (the ratio of λ_1 to λ_2 is 8 ~ 14, the maximum number of evolution generation permitted is 40). Fig. 3(a) shows the potential (ϕ) distribution under the optimization conditions while the AC voltage of electric plates is the highest; Fig. 3(b), (c) shows the SAR distribution and the temperature(T) distribution, respectively. The heating time for all cases was 900 s. The ultimate average temperature and its deviation for the heating target were 43.8 and 1.9℃, respectively; those for the non-target were 38.0 and 1.2℃; the consumed power was 2260 W. And the bold lines around the boundary showed the locations and sizes of the two electric plates. It could be concluded that via optimization the expected goals of hyperthermia were approximately achieved.

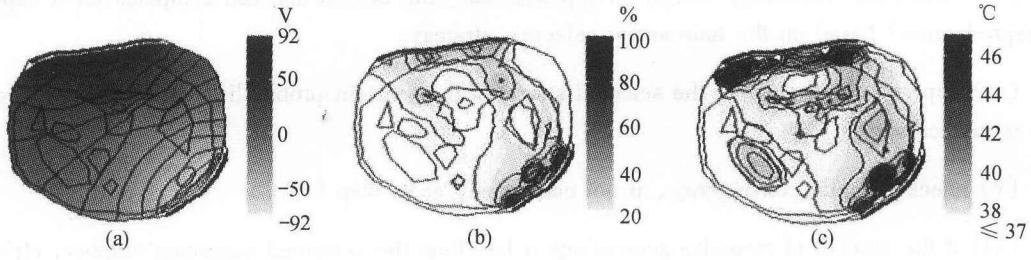


Fig. 3 Potential (ϕ) distribution (a), SAR distribution (b), and temperature (T) distribution (c) under the optimization conditions for the case of shallow-seated tumor.

Figure 4 shows the optimization result in the case of deep-seated tumor hyperthermia. The ultimate average temperature and its deviation for the heating target were 42.8 and 2.0℃, respectively; those for the non-target 38.1 and 1.2℃; the consumed power was 2820 W (higher than that in the case of shallow-seated tumor). Just as expected, the optimization result for deep-seated tumor was not so good as that for shallow-seated tumor, but the requirement of heating object was satisfied. However, the local overheating of normal tissues could not be ignored. A better optimization result might be obtained if the increasing effect of blood perfusion rate in the heated normal tissues was considered. The more successful optimization hyperthermia result in shallow-seated tumor case might be due to the fact that the RF-capacitive hyperthermia is more suitable to heat superficial tissues. In addition, the optimization hyperthermia process in the shallow-seated tumor case seemed more promising for the spatial adjacency of the target (shallow-seated tumor) and the ultimate optimization parameters (the boundary potentials).

As shown in Fig. 5, the ultimate average temperatures and their deviations were 43.0 and 1.9℃, respectively for the shallow-seated tumor; 42.9 and 2.1℃ for the deep-seated tumor, and 38.2 and 1.4℃ for the normal tissues. The consumed power was 2920 W (higher than those in the case of only-one single tumor). In Fig. 5 it is shown that both deep- and shallow-seated tumors have been well heated but with some overheating in local normal tissues. An interesting outcome was that the optimization hyperthermia results of the two-tumor case exhibited superiority over those of only-one deep-seated tumor, which might be attributed to the concurrent optimizing motivation of the optimiza-

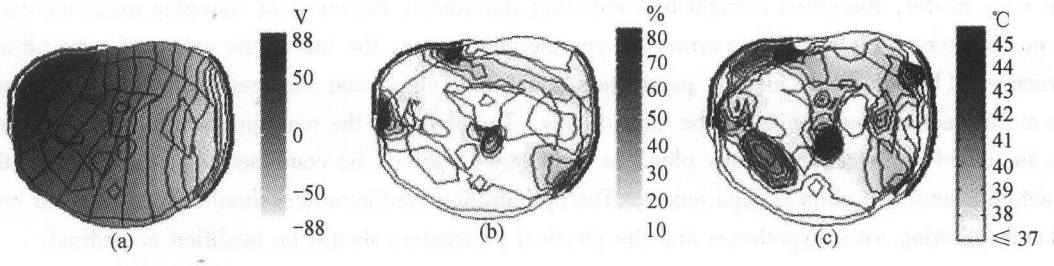


Fig. 4 Potential (ϕ) distribution (a), SAR distribution (b), and temperature (T) distribution (c) under the optimization conditions in the case of deep-seated tumor.

tion objects of the two tumors, where the deep-seated tumor could acquire optimum heating boundary potentials with the aid of shallow-seated tumor (on the boundary). In contrast, in the case of only-one deep-seated tumor, there were only constraints to avoid overheating of normal tissues on the boundary.

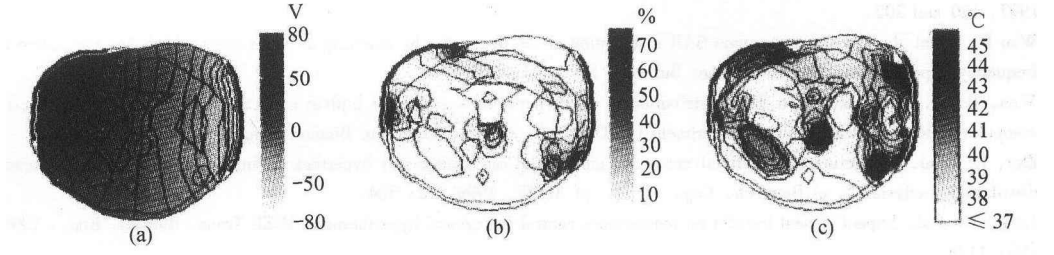


Fig. 5 Potential (ϕ) distribution(a), SAR distribution (b), and temperature (T) distribution (c) under the optimization conditions in the case of both deep- and shallow-seated tumors.

The weight coefficients λ_1 and λ_2 should be selected carefully, considering the contradictory requirements of heating tumor tissues and protecting normal tissues. If λ_1 and λ_2 were chosen too close to each other, the optimization process may proceed too tardily to offer a valuable scheme. In this paper, the ratio of λ_1/λ_2 has been set between 8 and 14 through trials.

5 Conclusions

In this paper, an original method of heating parameter optimization is discussed based on genetic algorithms in RF-capacitive hyperthermia. In the simulation of the tissue model resembling the real body structures, satisfactory temperature distributions for expected hyperthermia target have been found. Though only the implementation instances for the biplate RF-capacitive hyperthermia device and constant blood perfusion rate are given, these optimization conception and chief procedures can also be adopted to the triplate device and the situations where the temperature-dependent variation of blood perfusion rate is considered. (The simulation results in these situations will be discussed in subsequent papers.)

On the other hand, the results of biological numeral computation are certainly more or less different from realities. These differences come from a variety of sources, such as the inaccuracy of simula-

tion body model, the errors brought by computing algorithms, the constant changing influence caused by environments, the systematic errors of hyperthermia device, the inaccurate values of some physical parameters (blood speed, electric parameters of tissues, etc.) and the inadequate understanding of the multi-feedback mechanism of the human body. Therefore, in the real application of hyperthermia, the simulated optimization therapy plan, as a reference, should be combined with the considerations of actual events and clinical experiences. The optimization configurations should be adjusted or recalculated following some hypotheses and the physical parameters should be modified accordingly.

We firmly believe that further research on the optimization technique for body temperature field control is of considerable scientific importance to hyperthermia. And this technique is helpful for designing the hyperthermia device and improving the clinical therapy plans for hyperthermia.

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