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ADAPTIVE CONTROLLER FOR HYPERTHERMIA ROBOT*

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ABSTRACT

This paper describes the development of an adaptive computer control routine for a robotically, deployed focused, ultrasonic hyperthermia cancer treatment system. The control algorithm developed herein uses physiological models of a tumor and the surrounding healthy tissue regions and transient temperature data to estimate the treatment region's blood perfusion. This estimate is used to vary the specific power profile of a scanned, focused ultrasonic transducer to achieve a temperature distribution as close as possible to an optimal temperature distribution. The controller is evaluated using simulations of diseased tissue and using limited experiments on a scanned, focused ultrasonic treatment system that employs a 5-Degree-of-Freedom (D.O.F.) robot to scan the treatment transducers over a simulated patient. Results of the simulations and experiments indicate that the adaptive control routine improves the temperature distribution over standard classical control algorithms if good (although not exact) knowledge of the treated region is available. Although developed with a scanned, focused ultrasonic robotic treatment system in mind, the control algorithm is applicable to any system with the capability to vary specific power as a function of volume and having an unknown distributed energy sink proportional to temperature elevation (e.g., other robotically deployed hyperthermja treatment methods using different heating modalities).

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I. INTRODUCTION

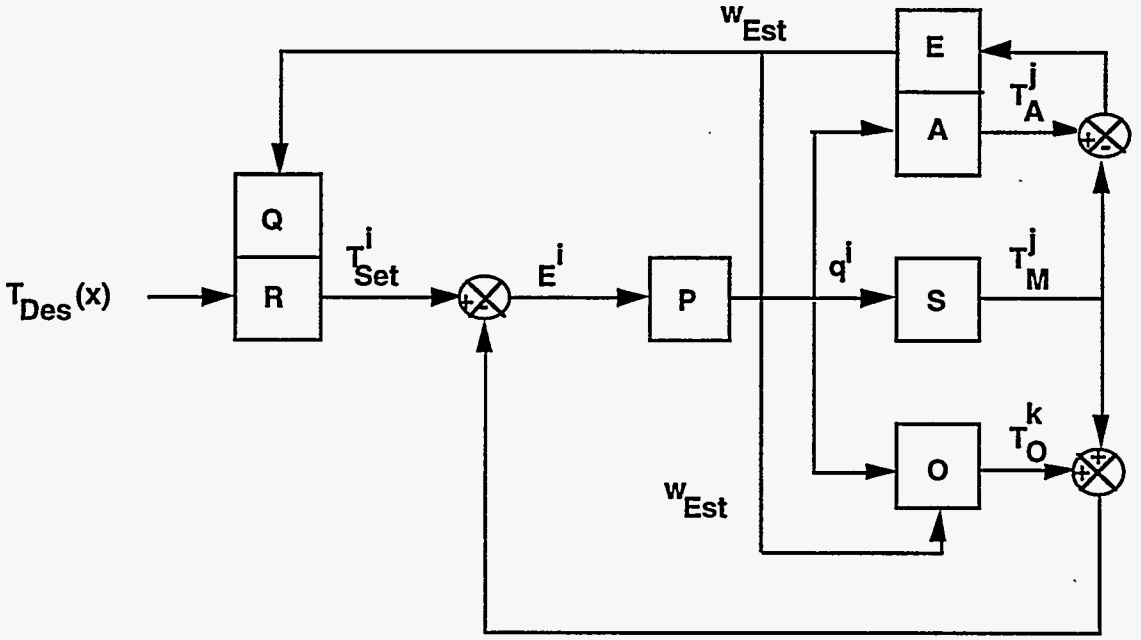
Treatment of cancer with elevated temperatures (hyperthermia) has been used successfully in the clinic. Effectiveness of the treatment is highly dependent upon the temperature profile achieved within the tumor. However, care must be taken not to damage healthy tissue, especially for tumors seated deep within healthy regions through which the thermal energy must pass. Focused ultrasonic transducers can be used to treat deep-seated tumors because the specific power (power per unit volume) is not high except in the focal region of the transducer. If the treatment volume is large relative to the focal volume of the transducer, then the transducer may be scanned throughout the treatment volume to heat the entire region. This is often done with robotic mechanisms. (For example, a 5-D.O.F. robot can scan a circular, focused ultrasonic transducer's power profile through any portion of a three-dimensional volume at any arbitrary orientation.) Because the removal of thermal energy from highly perfused tissues (like tumors) is dominated by the energy removed from blood flow, control of the specific power distribution profile to produce an effective temperature distribution is dependent upon not only the specific power profile of the transducer and the scanning pattern but is also strongly dependent upon tumor blood perfusion profiles. Many control routines in the past have controlled temperatures at limited positions. Less than ten temperature sensors is typical.[1,2]

This paper describes the development of an adaptive computer control routine that uses physiological models of the tumor and the surrounding healthy regions and transient temperature data to estimate the treatment region's blood perfusion. This estimate is used to vary the specific power profile of a scanned, focused ultrasonic treatment system to achieve a temperature distribution

standard proportional-integral-derivative (PID) controller using simulations of diseased tissue and using limited experiments on a scanned, focused ultrasonic treatment system that employs a 5-D.O.F. robot to scan the treatment transducers over a simulated patient.

II. APPROACH

First generation hyperthermia heating systems are capable only of varying the power distribution as a function of time. Second generation systems are capable of varying power as a function of space and time. Three adaptive control routines (AD1, AD2, AD3) were developed for a second generation hyperthermia heating system.[3] Each of these schemes is made adaptive by estimating the blood perfusion distribution within the treated region with respect to space and time; however, each of the three routines uses the estimated perfusion in a different manner. Each relies on a conventional PID algorithm as the core controller with the following adaptations: AD1 estimates an optimal set of set-point temperatures; AD2 uses the estimate to model and control unmeasured locations; and AD3 estimates an optimal set of set-point temperatures and controls unmeasured locations. All of the algorithms can be described in a single block diagram shown in Fig. 1; however, because of the limited space, this paper will focus on the adaptive controller AD1. The goal of the adaptive controller AD1 is to estimate the set-point temperatures for a conventional PID control algorithm which will produce a specific power deposition profile that will give a temperature distribution as close as possible to an ideal desired temperature distribution. To achieve this goal, the routine must estimate blood perfusion for a thermal model of the treatment experiencing a transient temperature decay, use the treatment thermal model with the estimated perfusion to estimate an optimal specific power deposition profile, and again use the thermal model to solve for the actual set-point temperatures to command to the PID routine, which



Legend for Fig. 1

M = Number of sensors
N = Number of power (control) regions
i = Index for number of power regions in the control algorithm (1+N)
j = Index for number of measured temperatures, i.e., sensors (1 through M)
k = Index for number of estimated temperatures (M+1 through N)
Note: When N=M the observer is not used; thus index i and index j cover the same range and k is not needed.
x = Spatial vector of all nodes
T_{Des} = Desired temperature
T_{Set} = Set-point temperatures at N locations: [M sensors => (N-M) observed temperatures]
T_A = Model temperatures at M sensor locations
T_M = Measured temperatures at M sensor locations
T_O = Estimated temperatures at (N-M) nodal locations

$$E^i = \text{Error at N locations} = \begin{Bmatrix} T^j_{Set} - T^j_M \text{ for } j = 1 \rightarrow M \\ T^k_{Set} - T^k_O \text{ for } k = M+1 \rightarrow N \end{Bmatrix}$$

q^i = System specific power in N regions termed power regions in Table 2 (W/m^3)
q_{Est} = Estimated specific power vector in N regions (W/m^3)
w_{Est} = Estimated perfusion vector in W regions (kg/m^3-s). The number of perfusion regions is unrelated to the number of power regions or the number of sensors.

Fig. 1. Block Diagram Illustrating the Structure of the Adaptive Control Routine (AD1).

will produce the specific power profile previously optimized. Since the basis of the adaptive controller is a PID routine with only the set-points being changed, the routine is inherently stable. Each block will be described next for the adaptive control routine AD1.

Block Q: Block Q is a Gaussian estimation routine[4] that optimizes the magnitudes of the spatial distribution of the specific power (q_{Est}) to yield a temperature distribution that approximates a desired temperature distribution, $T_{Des}(x)$, to a specified tolerance for a preselected cost criterion. This routine was developed by Clegg.[5] A typical desired temperature distribution and the one used throughout this study is therapeutic temperature (43°C) in the tumor tissue and arterial temperature (37°C) in the normal tissue. This distribution is impossible to obtain in practice, so the Gaussian estimation routine optimizes the spatial distribution of the specific power to achieve a temperature distribution as close as possible to this ideal.

Block R: Block R is a reference model of the energy transport in the tissue regions being treated. This model contains tissue thermal properties, estimated blood perfusion (w_{Est}), and the optimized specific power profile (q_{Est}). This block produces the set-point temperatures (T_{Set}^i), which, when used with a conventional PID routine controlling the thermal system modeled as described (tissue properties, estimated perfusion, optimized specific power), will produce a specific power deposition profile as close to the optimized profile as possible.

Block P: This is the standard PID control routine. The input is the error signal (E^i) calculated as the difference between the set-point temperatures obtained from block R (T_{Set}^i) and the measured temperatures (T_M^j). The output is the magnitude of the spatial power distribution (q^i).

Block S: This is the system being controlled by the controller. For analysis, this is a simulated patient/simulated heating system; for experiments, this is a phantom patient/actual heating system; and for treatment, this is the actual patient/clinical treatment system. The actual specific power profile (q^i) is the input, and the outputs are the actual temperatures (T^j), some of which are measured (T_M^j).

Block E: Block E functions as the adaptation mechanism for the adaptive control schemes. It consists of a Gaussian estimation algorithm (same algorithm used in block Q), which estimates the spatial distribution of the perfusion field (w_{Est}), which gives agreement between the temperature decay following a power-off transient as predicted by a

treatment model (T_A^j as a function of time) and the actual temperature decay (T_M^j as a function of time) measured by temperature sensors located in the treated tissue (or simulated treated tissue in the case of the controller operating on models).

Block A: Block A is the adjustable model used by the Gaussian estimation routine (block E) to predict the tissue temperatures following a power-off transient for the adaptive control routine AD1. The trial perfusion field from block E and the actual spatial power distribution calculated by block P are the inputs to this block. The output is the predicted temperature field (T_A^j) for the temperature decay following a power-off transient.

Block O: Block O is an observer not used in either the PID or the AD1 formulation but is used in the AD2 and AD3 formulations.[3]

A summary of the AD1 controller information for each block is presented in Table 1 along with a comparison to what the blocks would be for a conventional PID controller.

III. RESULTS

The conventional PID routine and the adaptive control routine AD1 were evaluated using simulated treatments and with limited experiments. The results of these evaluations follow.

A. Simulations

The PID routine and the adaptive controller AD1 were evaluated with one-dimensional computer simulations of a treated region. Each simulation modeled the thermal transportation of energy using the bioheat transfer equation developed by Pennes,[6] which was solved using spectral methods. The computer used for the controller and for the simulations was a VAX 8600. For a complete description of the thermal model and the numerical solution technique, the interested reader is referred to Kress.[3] (Spectral methods were chosen for their speed of solution.) The healthy tissue and the tumor were modeled with 33 nodes, which translates into 16 Fourier coefficients in the spectral technique after antialiasing is applied. This was sufficient to model the one-dimensional system and allow for estimation of the blood perfusion within the time frame of a treatment. A summary of the tissue models, the perfusion regions, the power deposition (control) regions, and the location of simulated temperature sensors (marked by X's) is presented in Table 2.

Table 1. Block diagram information for adaptive controller AD1 as compared to a conventional PID controller.

Type	Q	R	P	S	E	A
N=M PID	1	Filter	PID	System	-	-
Input	$T_{Des}(x)$	$T_{Des}(x)$	E^i	q^i		
Output	$T_{Des}(x)$	T_{Set}^i	q^i	T^j		
N>M ADI	Power Estimator	Model q Variable	PID	System	Perfusion Estimator	Model w Variable q^i
Input	$T_{Des}(x)$	w_{Est}, q_{Est}	E^i	q^i	$(T_M-T_A)^j$	
Output	q_{Est}	T_{Set}^i	q^i	T^j	w_{Est}	T_A^j

Table 2. Summary of tumor blood perfusion models, power deposition regions, and sensor locations (X) for simulated treatments.

		Tissue Types																							
		Normal				Tumor (necrotic core, highly perfused periphery)																Normal			
Nodes		1	2	7	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	27	32	33
Blood perfusion	LC	1				2					0					2					1			
	LT	$1(2-e^{-t/\tau})$				$2(2-e^{-t/\tau})$					0					$2(2-e^{-t/\tau})$					$1(2-e^{-t/\tau})$			
	HC	1				5					0					5					1			
	HT	$1(2-e^{-t/\tau})$				$5(2-e^{-t/\tau})$					0					$5(2-e^{-t/\tau})$					$1(2-e^{-t/\tau})$			
Power regions	3	X				X															X			
	4	X							X						X						X			
	5	X					X					X						X			X			
	6	X					X				X			X				X			X			
	7	X				X			X				X			X			X		X			
	8	X				X			X		X			X		X			X		X			
	9	X				X		X		X			X			X		X		X	X			
	10	X				X		X		X	X			X		X		X		X	X			
Nodes		1	2	7	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	27	32	33

Notes for Table 2:

1) Blood perfusion units are kg/m^3-s, τ is the time constant (720 s), t is time (s).
2) Blood perfusion acronyms:
   LC = Low flow, Constant with respect to time.
   LT = Low flow, Time varying.
   HC = High flow, Constant with respect to time.
   HT = High flow, Time varying.
3) Control regions are where specific power levels can change.
4) X indicates location of simulated temperature sensor.
5) All models have 33 nodes (i.e., 32 Fourier modes with 16 kept after antialiasing).
6) Nodes 3, 4, 5, 6, 8, 26, 28, 29, 30, and 31 not shown to save space; they are similar to nodes in the same region.
7) Treatment time of 1 hr, tissue length (normal, tumor, normal), 10 cm.

The performance of both controllers was evaluated using an Integral Square Error (ISE) approximated numerically by:

$$ISE = \sqrt{\frac{1}{N\tau}\frac{1}{N+1}\sum_{j=1}^{N\tau}\sum_{i=1}^{N+1}\left(T_i^j - T_{Des\,i}^j\right)^2}\quad , \qquad (1)$$

where T_i^j is the temperature at node i at time step j, $T_{Des\,i}^j$ is the desired temperature at node i at time step j, N+1 is the number of nodes (33), and Nt is the number of time steps in the simulation. The ISE has units of ^oC and is a single number that can be used to quantify the performance of a particular controller for a given treatment. The ISE has an ideal value of 0.48 ^oC for a 33-node (32-mode) Fourier transform.

Table 3 compares the performance of the PID and AD1 routines for the one-dimensional simulations of the treatments described in Table 2. The ISE of Eq. (1) is used as a measure of performance. The simulated treatments last for 1 hr., the treated region is 10 cm long (normal to tumor to normal), and the tissue thermal properties are: thermal conductivity of 0.583 W/m-^oC, density of 1000 kg/m^3, and specific heat of 4200 J/kg-^oC.

Table 3. ISE (°C) for PID and AD1 controllers for 33-node, one-dimensional simulated tumor models LC, LT, HC, and HT described in Table 2. Sensor locations and power deposition regions are shown in Table 2 as well.

Model		LC		LT		HC		HT	
Controller		PID	AD1	PID	AD1	PID	AD1	PID	AD1
No. of	3	1.687	1.697	1.936	1.969	2.102	2.173	2.399	2.478
R	4	1.474	1.542	1.694	1.743	1.940	1.885	2.546	2.322
e	5	1.338	1.395	1.166	1.310	1.366	1.449	1.195	1.442
g	6	1.338	1.378	1.166	1.294	1.366	1.457	1.195	1.436
i	7	1.649	1.307	1.428	1.333	1.637	1.407	1.410	1.484
o	8	1.649	1.288	1.428	1.325	1.637	1.386	1.410	1.488
n	9	1.648	1.257	1.428	1.188	1.636	1.284	1.412	1.367
s	10	1.648	1.245	1.428	1.185	1.636	1.290	1.412	1.373

Notes for Table 3:

1) Number of regions = number of temperature sensors.
2) Ideal Integral Square Error (ISE) calculated by a 33-node (32-mode) Fourier transform of the ideal temperature distribution [i.e., therapeutic temperature (43°C) in the tumor tissue and arterial temperature (37°C) in the normal tissue] is 0.48°C.

The results of Table 3 show that the adaptive control routine AD1 generally performs better than the conventional PID routine and always performs better for the cases with a large number of regions (e.g., 9 and 10).

B. Experiments

A limited number of experiments were performed with the robotically deployed, scanned, focused ultrasonic system[7] and a phantom patient developed and described.[3] The phantom patient consisted of a preserved dog kidney as a simulated healthy tissue/tumor perfused by a peristaltic pump. The optimization computer (VAX 8600) was not connected to the clinical treatment, system so the optimized set-point temperatures were determined off-line and used in the conventional PID controller. The performance of the PID controller and adaptive controller AD1 were compared by calculating the normalized temperature for all of the measured locations defined by the difference between the measured temperatures (T_M) and the arterial temperature ($T_{Arterial}$), divided by the difference between the set-point temperature (T_{Set}) and the arterial temperature.

$$T_N = \frac{T_M - T_{Arterial}}{T_{Set} - T_{Arterial}} . \qquad (2)$$

Clearly, T_N equal to 1 is ideal. A typical experiment showed improved performance of the adaptive routine over the conventional PID. For example, in a highly perfused region, T_N went from 0.3 for the PID to 0.5 for AD1, and in a region of relatively low perfusion T_N went from 1.5 for the PID to 1.1 for AD1.

IV. CONCLUSIONS

Results of the simulations and experiments indicate that the adaptive control routine improves the temperature distribution over standard classical control algorithms if good (although not exact) knowledge of the treated region is available. Although developed with a scanned, focused ultrasonic robotic treatment system in mind, these algorithms are applicable to any system with the capability to vary specific power as a function of volume and having an unknown distributed energy sink proportional to temperature elevation (e.g., other robotically deployed hyperthermia treatment methods using different heating modalities).

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