Real-Time Prediction of Temperature for Electromagnetic Heating Therapy in Deep-Seated Tissue

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This paper aims to develop a model for predicting the temperature response of tissues in the electromagnetic heating therapy (EHT) when using a magnetic flux concentrator to improve the heating efficiency. Since the EHT has two critical challenges when applied to deep-seated tissue heating: 1) the temperature could not be accurately measured and 2) the magnetic field intensity would decrease with increasing depth. Finite element method (FEM) is suitable for the coupled analysis with electromagnetic fields and heat transfer, it could be used to predict the temperature profiles in deep tissue implanted by magnetic materials. An adaptive network fuzzy inference system (ANFIS) model is further implemented based on the simulated data generated by FEM model. The real-time data acquisition would be able to predict the dynamic maximum temperature of tissues by ANFIS model in the treatment process.

***Index Terms*—Electromagnetic induction, finite element analysis, fuzzy neural networks, prediction methods.**

I. Introduction

ELECTROMAGNETIC heating therapy (EHT) has been considerably concerned in the past decades. Furthermore, the relevant research is rapidly increasing, particularly on the tumor ablation issue. Among such technologies, magnetic mediated hyperthermia (MMH) has great potential for deep tumor treatments is due to selective induction heating in high magnetic permeability material, which is implanted in human bodies, and conducting heat to the surrounding lesion regions. Magnetic materials could be ferrofluid [1]–[3], thermal seed [4], or needle [5]. The needle shows the best heat-producing capability, with the volume is the largest. In contrast, ferrofluid is poorer heating, but it could expand the heat conduction area. The magnetic field intensity would decrease at the deeper positions, causing insufficient heat production and non-uniform temperature distribution, both of which are regarded as inevitable. The continuing improvements in induction coil had led to deeper effective treatment range [5] and uniform magnetic flux density [6] in medical applications.

Since the modeling of biological tissue temperature field is complicated. Finite element method (FEM) would obtain the approximation solution of mathematical model to reconstruct the biological tissue heat conduction characteristics and determine the temperature distribution. It offers the useful information for a real-time monitoring to avoid the extremely high temperature resulting in decreasing the heating area of tissue. A simplified temperature prediction model is proposed by using adaptive network fuzzy inference system (ANFIS) in this paper. The FEM model generated simulation data are the basis for ANFIS model, which is trained by finite data.

II. Modeling of Temperature Prediction

A. FEM Model Analysis

Figure 1 demonstrates the profile of the EHT in deep seated tissue. The depth could be defined as between induction coil and thermocouple, which is placed in the deep seated tissue. In the treatment process, the alternating current is passed through the induction coil to generate an alternating magnetic field. The needle for treatment is heated by induced eddy currents through internal conduction.

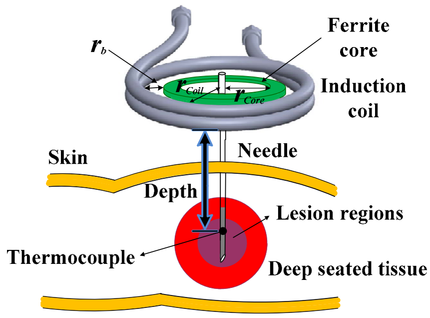

Fig. 1. A cross-sectional diagram of the EHT.

In the quasi-static approximation, Maxwell's equations are applied to deriving the governing equation, which includes electric scalar potential, **V**, and magnetic vector potential, **A**, are calculated as follows:

$$\nabla \times (\mu^{-1} \nabla \times \mathbf{A}) = -\sigma \frac{\partial \mathbf{A}}{\partial t} - \sigma \nabla \mathbf{V} \tag{1}$$

where μ and σ are the magnetic permeability and the electrical conductivity. When the magnetic flux changes with single frequency, i.e. the induction coil carrying sinusoidal wave current with the angular frequency, ω, the eddy current density is denoted as [7]

$$\mathbf{J}_e = -\sigma(j\omega \mathbf{A}_0 + \nabla \mathbf{V}) \tag{2}$$

The heat source is generated by eddy current is written as

$$\mathbf{Q} = \left|\mathbf{J}_e\right|^2 / 2\sigma \tag{3}$$

The transient heat transfer equation with eddy current losses in three dimensions is represented as

$$\rho C \frac{\partial T}{\partial t} - \nabla \cdot (\lambda \nabla T) = \mathbf{Q} \tag{4}$$

where ρ, C and λ are the material density, specific heat capacity and thermal conductivity, respectively.

B. Modeling Based on ANFIS

Takagi-Sugeno fuzzy model is composed of IF-THEN rules, premise part and consequence part [8]. Piecewise linear approximation method to build the model using input-output data from the system, and the fuzzy rules are denoted as below:

$$\textbf{IF}\ x_1 \text{ is } M \text{ and } x_2 \text{ is } K,\ \textbf{THEN}\ z = g(x_1, x_2) \tag{4}$$

where x_1 and x_2 are inputs, z is output, M and K are fuzzy sets, and g is the polynomial function.

III. Magnetic Flux Concentrator Design

The induction coil with magnetic materials is capable of decreasing the magnetic reluctance of air gap, thereby concentrating stray flux does lead to increase magnetic flux density around the magnetic material. The temperature evaluation has been carried out using the commercial software COMSOL to solve the coupled field problem. The heating efficiency is defined as

$$\eta = \frac{T_x - T_n}{T_w - T_n} \tag{5}$$

where T_x is the steady-state temperature under different gaps between ferrite ring core and induction coil, r_b (Fig. 1), T_w is the steady-state temperature in the case of a coil filled with a solid ferrite core and T_n is the steady-state temperature in the case of a coil without ferrite core. Fig. 2 shows the heating efficiency for various values of gap (with different ferrite ring core size). The heating efficiency is greater than 0.93 could be obtained when the gap is 10 to 15 mm. The ferrite ring core size can then be considered as the optimal.

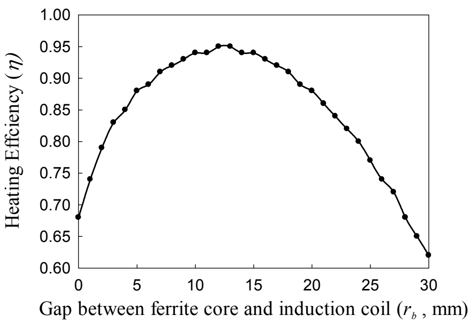

Fig. 2. Heating efficiency is dependent on the gap between ferrite core and induction coil.

IV. Experimental Results

The SUS420 stainless needle is inserted the *in vitro* porcine liver tissue for heating, with the total experimental period of 300 seconds. The temperature is monitored by the R-type thermocouple with the fine wire. The peak current on the induction coil could be adjusted from 250 to 750 A, and the operating frequency from 35 to 100 kHz. Fig. 3 presents the temperature response at two different depths for testing. One is 40 mm as shown in Fig. 3(a), the other is 70 mm in Fig. 3(b). The results are fairly consistent between ANFIS and FEM models. With the sampling time is one second, the results of sum absolute errors (SAE) are presented in Table I.

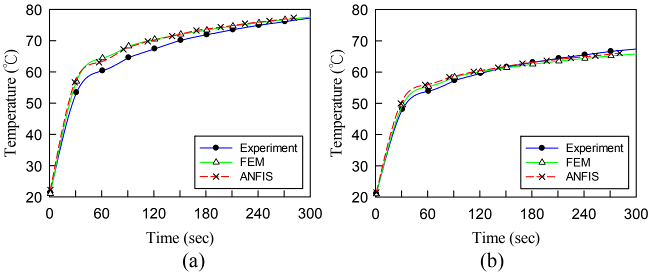

Fig 3. Temperature response curves of two modeling methods and *in vitro* experiment by using the porcine liver tissue at different depths. (a) 40 mm and (b) 70 mm

TABLE I
THE SAE AS RESIDUALS BETWEEN EXPERIMENTAL DATA AND TWO MODELS (ANFIS AND FEM) CORRESPONDING DATA

Depth	Model	
	ANFIS (SAE)	**FEM** (SAE)
40 mm	662.63	652.67
70 mm	299.70	292.62

V. Conclusion

In this paper, two models (FEM and ANFIS) are developed to predict the temperature response of deep-seated tissue in the EHT as well as analyzing heating efficiency of the magnetic flux concentrator. The FEM model has the advantage of tissues temperature distribution being observable, and it would provide a numerous training data feeding into ANFIS. However, the ANFIS model is a relatively simple mapping relationship between depth and dynamic temperature. It could make the speed of prediction is remarkably fast. The adequate results have demonstrated that these temperature prediction models could be practically implemented.

VI. References

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