Neural Networks Modeling of Temperature Field Distribution in Hyperthermia

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Abstract

Hyperthermia is known to be a method of killing tumor cells by heating. Ultrasound transducer is often used to be the heating device. In order to kill the tumor cells and not to injure the normal tissue, the temperature distribution generated by ultrasound must be predetermined. For a multi-element ultrasound transducer, the phase and the amplitude of the input signal for each element can be tuned to generate a suitable temperature distribution to meet the needs of individual treatment. However, direct computation is often time-consuming. While there are also difficulties in solving the ultrasound transducer parameters with a given temperature distribution. In this paper, artificial neural networks are used to learn the relationship between the ultrasound transducer parameters and the temperature distribution, both in the forward and the inverse directions.

1. Introduction

The effect of hyperthermia is based on the observation that if the tissue temperature is heated to 43°C for 30-60 minutes, the surviving tissue cells will be less than one thousands[1]. Thus, a properly designed temperature distribution could achieve the objective of killing the tumor cells and not injuring normal tissue. Multi-element ultrasound transducer is often used to be the source of heating. The amplitude and phase of the input signal for each element can be tuned to derive a suitable power intensity distribution[2][3]. Then a temperature field can be set up within the tissue

to perform hyperthermia treatment. The calculation of the temperature field is very time-consuming and is unrealistic if real-time adjustment of treatment planning is desired. As a result, the neural networks modeling of the ultrasound temperature field seems to be a solution for determining the relationship between the inputs of the ultrasound transducer and the temperature field created.

2. Ultrasound Transducer

The ultrasound transducer used in this paper has two elements, the inner disk (with diameter 0.75cm) and the outer ring (with diameter 1.5cm). The amplitudes of the input power and the phase between the two elements can be tuned. According to the assumption of uniform tissue characteristics and the circular transducer, temperature distribution is symmetric to the axis that is perpendicular to the transducer surface and is through the transducer center. A typical temperature distribution by direct calculation with the related equations is shown in figure 1. The sampling distance is 0.075cm, i.e. with totally 21x200 points.

Figure 1 The Typical Temperature Field

3. Temperature Field Modeling

The well-known perceptron-like multi-layer neural networks are used in the modeling of the temperature field in this paper. There is only one hidden layer, other than the input and the output layers. The learning algorithm is based on the back-propagation algorithm[4]. Its learning rate is often determined by trial and error.

Forward Model

The forward model is designed to emulate the relationship between the transducer inputs and the temperature field. The input parameters of the model are the signal amplitudes for the inner disk and the outer ring, and the their phase difference. The output variable is the temperature distribution (2100 points). Owing to the large number of output variables, 21 neural networks are used to reduced the size of the individual net. 80 data set were calculated to be used as the training data. After training with the training data set, 10 randomly chosen data were used as the testing data sets. The result of the testing data is shown in table 2. The Root-Mean-Square(RMS) errors of the 10 cases demonstrated that the errors are within very acceptable ranges. Actually, the RMS error is less than 0.14 °C even in the worst case (case 6). Note that the average temperature elevation in percentage is rather high for case 9, even though its RMS error is only 0.06984 °C. This data may be caused by the fact that its maximum temperature elevation is only 0.94 °C. (The base temperature is 37 °C in our calculations.)

The above result shows that the idea of using neural networks for temperature field modeling in hyperthermia is feasible. The most important advantage of using the neural networks modeling is really not on its accuracy, but on the its computation speed. The training time for a neural network is usually long. However, its computation of the temperature fields only takes 0.06 sec with a Pentium 90 CPU after training. Such a speed will enable us to consider real-time adjustments of treatment planning, or we can call it “dynamic treatment planning”.

	RMS Error	Average Temperature Elevation (%)	Upper Bound of Error	Lower Bound of Error	Max. Temp
Case 1	0.07572	1.947% (3.222)	0.0915	-0.3071	44.01
Case 2	0.06989	7.816% (0.9075)	0.1739	-0.1049	39.88
Case 3	0.11490	12.60% (0.8341)	0.1984	-0.4412	40.44
Case 4	0.07160	2.097% (3.057)	0.1912	-0.1636	42.38
Case 5	0.05257	2.211% (1.924)	0.06136	-0.2504	41.30
Case 6	0.13910	4.495% (2.495)	0.4486	-0.2845	42.07
Case 7	0.05621	5.154% (0.8556)	0.1900	-0.05731	38.65
Case 8	0.04142	0.9854% (4.303)	0.1414	-0.07943	46.05
Case 9	0.06984	27.16% (0.2741)	0.1735	-0.004953	37.94
Case 10	0.03920	1.211% (3.429)	0.05792	-0.1276	45.04
Average	0.07896		0.17278	-0.1821	

Table 1 Testing Result for the Forward Model

Inverse Model

The inverse model is designed to establish the relationship between the temperature field and the transducer inputs, i.e. to determine the proper transducer inputs which can form a desired temperature field. The structure of the neural network used is similar to the forward case, except the inputs and the outputs are reversed. For the inverse case, it is observed that the number of data for the temperature field needed for establishing the relationship is not as high as in the forward case. Instead of using 2100 points, only 4x15 (60) points are used.

The result with the testing data set is shown in table 2. As we can see that the error of the estimated particle velocity seems to be related to the magnitude of the velocity. The higher the particle velocity is, the smaller the error. While in case 4, when the velocity for the inner disk is much smaller than the velocity of the outer ring, the

temperature field is dominated by the outer ring and the phase difference becomes insignificant. As a result, the error for the phase difference is large. However, we will show in below that the phase difference plays very little role in such a case and is literally insignificant. In case 2 and case 9, it is also observed that the phase differences are out of the range of training set and the error become large.

	Particle Velocity of Outer Ring	Reference	Particle Velocity of Inner Disk	Reference	Phase Difference	Reference
Case 1	3.79	3.84	1.55	1.76	1.20π	1.06π
Case 2	0.37	0.80	2.80	2.64	1.43π	0.18π
Case 3	0.08	0.92	2.80	2.88	1.49π	1.30π
Case 4	3.78	3.76	0.09	0.08	1.44π	0.84π
Case 5	2.87	2.92	1.96	1.96	1.42π	1.40π
Case 6	2.82	2.72	2.84	3.00	1.86π	1.82π
Case 7	1.94	1.96	0.32	1.08	1.65π	1.52π
Case 8	3.99	4.00	2.32	2.24	0.48π	0.52π
Case 9	0.05	0.32	0.97	1.56	1.53π	0.10π
Case 10	3.69	3.72	3.18	3.16	1.49π	1.48π

Table 2 Testing Result for the Inverse Model

It is pretty obvious that different transducer inputs may construct the same temperature field within our error tolerance. Therefore, the inverse model may be usable even if its outputs deviate from the reference values. As a matter of fact, the inverse model is "correct" if the transducer inputs calculated by the neural networks can form the desired temperature field. Two different verification approaches are used to verify the data in table 2. The ID method is to compare the reference temperature field with the field derived through inverse model plus direct

computations. The IF method is to compare the reference temperature field with the field derived through inverse model plus the forward model. The average RMS error for the ID method is 0.14899 and is 0.16455 for the IF method. To be noticed that the IF method has an error only slightly higher than the ID method and is still in the acceptable range.

4. Conclusion

The forward model and the inverse model of the temperature field in hyperthermia are shown in this paper. Multi-layer neural networks are adopted for modeling and have the advantage of real-time computation after proper training. Both models achieve excellent performance with very acceptable accuracy. Although the inverse model may not derive the exact reference values, its corresponding temperature fields are still very similar to the reference ones. The fast computation of the temperature field in hyperthermia creates the possibility of the real-time adjustment of the treatment planning, *i.e.* as we call it, the dynamic treatment planning.

Reference

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