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Temperature models of a homogeneous medium under therapeutic ultrasound

Modelos de temperatura de um meio homogêneo sob ultra-som de terapia

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Abstract:
Temperature modelling of human tissue subjected to ultrasound for therapeutic use is essential for an accurate instrumental assessment and calibration. The existence of accurate temperature models would enable a safe and efficient application of the thermal therapies. The main objective of this work is the comparison between the performance of non-linear models and linear models for punctual temperature estimation in a homogeneous medium. The final goal of the work hereby reported is the construction of neural models for "*in-vivo*" temperature estimation. The linear models employed were AutoRegressive with eXogenous inputs (ARX), and the non-linear models used were radial basis functions neural network (RBFNN). The best-performed RBFNN structures were selected using the Multi-objective Genetic Algorithm (MOGA). The best performed neural structure present a maximum absolute error of 0.2 ºC, which is one order magnitude less than the one presented by the best ARX.
***Keywords*:** Temperature modelling, Neural networks, Multi-objective genetic algorithms, Ultrasound.

Resumo:
A modelagem da temperatura em tecidos humanos, quando os mesmos são sujeitos a ultra-som de terapia, é um aspecto essencial para um correto controle e calibração da instrumentação de terapia. A existência de modelos precisos possibilitaria um uso mais seguro e eficiente das terapias térmicas. O objetivo principal deste trabalho é a comparação entre a performance de um modelo linear e de um modelo não linear, na estimação pontual da temperatura num meio homogêneo. O objetivo final do trabalho é a construção de modelos para estimação in-vivo da temperatura. Os modelos lineares aplicados foram "autoregressive models with exogenous inputs" (ARX), enquanto que os modelos não-lineares aplicados foram "radial basis functions neural networks" (RBFNN). As melhores estruturas para as RBFNN foram selecionadas usando o "multi-objective genetic algorithm" (MOGA). A melhor estrutura RBFNN apresentou um erro máximo absoluto de 0,2 ºC, que é inferior em uma ordem de grandeza ao erro cometido pelo melhor modelo ARX.
***Palavras-chave*:** *Modelagem de temperatura, Redes neuronais, Algoritmos genéticos multi-objectivo, ultra-som.*

Introduction

Accurate determination of human tissue temperature is a fundamental aspect concerning the secure application of therapeutic ultrasound instrumentation in cancer treatment (Hyperthermia). The main impediment for the generalised clinical use of hyperthermia is the lack of accurate knowledge of localised temperature patterns in time and space, which would enable a lesion-less treatment.

Having in mind non-invasive temperature estimation in time and space, previous work in the field relates linearly the changes in sound velocity and medium expansion with changes in temperature. The temperature range considered was between 20 and 24 ºC, using a therapeutic transducer to induce heat, and a diagnostic transducer to extract characteristics (sound velocity and medium expansion) from the medium (Simon *et al*., 1998).

The main objective of the work hereby presented is to compare the performance of radial basis functions neural networks (RBFNN) versus linear ARX models, in punctual temperature estimation in a homogeneous medium radiated by therapeutic ultrasound. The temperature variation indicators considered were the amplitude of the fundamental component of the intensity spectrum, and the measured past temperature values. The final goal is to build a neural model to estimate the temperature variations in biological tissues under therapeutic ultrasound.

Materials and Methods

Data acquisition

The experimental setup used to collect data is presented in Figure 1 . The real data used in this work are temperature and acoustic intensity signals, in a point 48 mm distant (axial distance) from an ultrasonic therapeutic transducer, in a glycerine (homogeneous medium) tank. Data was acquired during approximately 110 min. At each 10 seconds a temperature value was recorded, as well as a window of 5μs of the acoustic intensity signal, corresponding to 2000 points of the intensity waveform.

Three sets of signals were acquired at 3 MHz in continuous operating mode, at three different intensities: 1 Watt/cm^2, 1.5 Watt/cm^2, and 2 Watt/ cm^2. The temperature ranges recorded are presented in Table 1. Glycerine was insonified only in the first 60 min, by the therapeutic device (Ibramed Sonopulse, São Paulo). During the remaining 50 minutes the acoustical energy was maintained at a zero level, while temperature variations were observed and recorded.

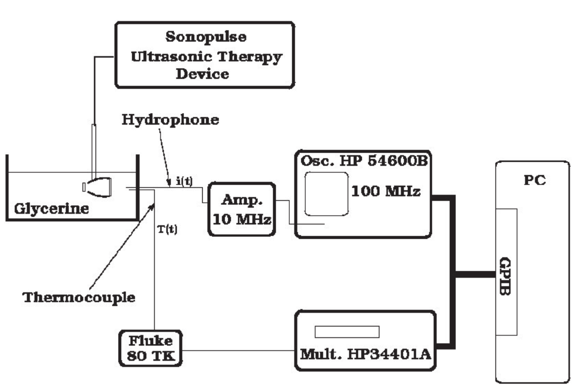

Figure 1. Experimental setup

Data processing

The construction of neural and ARX models requires the computation of features from the intensity signals in order to estimate temperature. In this paper only the fundamental component of the intensity spectrum, located at 3 MHz was computed.

Accurate development of neural and ARX models requires pre-processing of data. This phase normally encompasses a filtering operation followed by a normalisation operation. The filtering operation reduces the high frequency noise introduced by instrumentation. The normalisation is necessary to enable a correct training of the models. That is, the attainment of well conditioned models with a high capacity of generalisation (good performance in different situations). In this work the measured temperature and the fundamental component of the intensity spectrum present smooth waveforms, making unnecessary the filtering process. The temperature and the fundamental component of the intensity waveforms were normalised in amplitude between 0 and 1.

Generically, the construction of a neural model encompasses a training phase and a test phase. In the training phase the neural network parameters are computed. In the test phase the generalisation capacities of the obtained neural model are accessed, using a different data set. In this paper the data collected at 1 Watt/cm^2 was used for training, while the data collected at 1.5 Watt/cm^2 was used for testing.

RBFNN construction

An RBFNN is a three fully connected layers neural network. The first layer is a set of inputs, the second (hidden) layer is formed by a set of processing elements, called neurons. The outputs of the hidden layer

Table 1. Temperature ranges

Intensity	Initial Temp.	Maximum Temp.	Final Temp.
1.0 Watt/cm^2	29 °C	34.5 °C	28.5 °C
1.5 Watt/cm^2	30 °C	37.2 °C	28.0 °C
2.0 Watt/cm^2	31 °C	38.8 °C	31.0 °C

are linearly combined at the last layer to calculate the overall network output. The input/output relation for a RBF is given by:

$$f(x_j) = b + \sum_{i=1}^{n} \alpha_i \varphi\left(\left\| x_j - c_i \right\|\right) \quad (1)$$

where n is the number of neurons in the hidden layer, b is the bias term, ||.|| is a norm (an Euclidean norm was employed), and $\varphi\left(\left\| x_j - c_i \right\|\right)$ is a set of non-linear radial basis functions weighted by $\{\alpha_i\}_{i=1}^{n}$. The basis functions are centred at $\{c_i\}_{i=1}^{n}$(centres) and are evaluated at points x_j. Normally the basis functions are Gaussians (Teixeira *el al*., 2004):

$$\varphi_i(x_j) = e^{-\frac{1}{2\sigma_i^2}\left\| x_j - c_i \right\|^2} \quad (2)$$

In the construction of a RBFNN several questions arise (Ferreira *et al*., 2003): What is the appropriate number of neurons in the hidden layer? Which are the important input variables for a good model? What are the important lags of those variables? Which is the maximum lag to be considered?

The answers to these questions depend on the problem under study, are neither unique nor easy to find. The number of possible structures can be enormous, disabling an exhaustive search due to the necessary computational time. To solve this problem a multi-objective genetic algorithm (MOGA) (Fonseca and Fleming, 1996; 1998) was applied to select the best-fitted RBFNN structures.

The input variables considered for the RBFNN were the fundamental component of the intensity spectrum (I_m), and the measured temperature (T). The number of model inputs was restricted to the interval [2,30], while the possible number of neurons is an integer in the interval [2,15].

In this work the MOGA was defined to have 100 generations, of 100 RBFNN (individuals) each. The objectives to minimise were: training RMSE, test RMSE, maximum of the error auto-correlation (R_{ee}), and the maximum of the cross-correlation between the inputs and the error (R_{ue}). Having in mind the attainment of models with a high generalization capacity, the test RMSE was defined as a goal with value 0.003. The maximum of the correlation tests (R_{ee} e R_{ue}) was defined as a goal with value $CI = 1.96/\sqrt{N}$, where N is the number of points in the training set. If R_{ee} and R_{ue} have values inferior to CI then the models are considered adequate with 95% of confidence (Ferreira *et al*., 2003). In this work N = 377 and CI is approximately 0.1.

During the MOGA, the training of each individual was performed by the *Levenberg-Marquardt* (LM) algorithm, with the *Early-Stopping* termination criteria (Ferreira *et al*., 2003).

The MOGA parameters were: 10% of random immigrants (RBFNN), selection pressure (probable number of copies of the best individual) of 2, crossover rate of 0.7, and mutation rate of 0.5.

After the MOGA selection, the validation of the best individuals was performed with a third data set, called validation data. This data results from the measure at 2 Watt/cm^2 of intensity. Such as in the training and test data, normalization between 0 and 1 was performed.

ARX construction

The most used ARX model is defined by the following difference equation:

$$\begin{aligned} &y[t] + a_1 y[t-1] + \cdots + a_{na} y[t-na] = \\ &b_1 u[t-nk] + \cdots + b_{nb} u[t-nk-nb+1] \end{aligned} \quad (3)$$

This model relates the actual output y[t] with a finite number of values of the output y[t-k], and of the input u[t-k]. The structure of the model is completely defined by three parameters: number of poles (na), number of zeros (nb-1), and time delay of the system (nk). In this work $\{a_i\}_{i=1}^{na}$ and $\{b_i\}_{j=1}^{nb}$ coefficients were determined using the least squares strategy.

Results

This section presents the best models obtained with the MOGA, called preferable models (Ferreira *et al*., 2003), as well as the best-performed ARX model (linear model). The same data sets were used in both strategies.

The preferable set is formed by 11 models. The inputs and other characteristics of these models are presented in Tables 2 and 3, respectively.

Table 2. Inputs of the preferable models

Nº	Inputs (*Lags* of I_m and T)	
	I_m	T
1	4, 21, 25	1, 3, 5, 14, 32, 39, 41
2	0, 2, 4, 21, 27, 41	1, 5, 6, 11, 15, 22, 23, 29, 39, 46, 47
3	32, 35, 36, 37, 40	1, 5, 6, 7, 14, 15, 17, 19, 20, 22, 31, 35, 39, 43, 45
4	19, 22, 32	1, 6, 7, 20, 21, 28, 31, 35
5	9, 32, 39, 43	1, 6, 12, 15, 20, 21, 22, 24, 35
6	6, 32	1, 6, 20, 25, 29, 30, 34, 40, 43, 44
7	0, 26	1, 3, 6, 9, 15, 20, 28, 31, 41
8	0, 8, 20, 35	1, 3, 4, 6, 8, 9, 20, 28, 35, 40, 41, 46
9	0, 10, 42	1, 4, 5, 6, 8, 9, 31, 40, 42, 47
10	19, 45	1, 8, 13, 22
11	1, 29, 34	1, 4, 6, 8, 13, 14, 18, 23, 29, 35, 38, 45, 46

Table 3. Other preferable model characteristics and associated goals defined in the MOGA. (NA=Not Attributed).

Nº	Training RMSE	Test RMSE	R_{ee}	R_{ue}	||W||	# Neu.	Val. RMSE
1	0.0009	0.0034	0.1460	**0.0903**	4.8464	6	0.0083
2	0.0006	0.0047	0.1284	**0.0554**	1.4606	6	0.0081
3	0.0008	0.0135	**0.0818**	**0.0990**	11.997	15	0.0258
4	0.0009	0.0032	0.1441	0.1104	2.8490	4	0.0056
5	0.0009	0.0074	0.1180	0.1134	4.4526	13	0.0101
6	0.0009	0.0086	0.1016	0.1057	3.5580	6	0.0076
7	0.0007	0.0039	0.1328	**0.0609**	5.1444	6	0.0067
8	0.0006	0.0081	0.1254	**0.0656**	1.1145	10	0.0109
9	0.0006	0.0045	0.1314	**0.0647**	1.4266	6	0.0068
10	0.0009	0.0090	0.1200	**0.0723**	14,251	7	0.0131
11	0.0009	**0.0026**	0.1511	**0.0763**	9.9399	4	0.0027
Goal	**NA**	**0.003**	**CI=0.1**	**CI=0.1**	**NA**	**NA**	

The numbers in Table 2 are referred with the I_m and T lags. For example model number 10 has as inputs: I_m(k-19), I_m(k-45), T(k-1), T(k-8), T(k-13), and T(k-22).

The columns R_{ee}, R_{ue}, ||W||, #Neu, and Val. RMSE in Table 3 presents the maximum of the error autocorrelation, the maximum of the cross-correlation between the inputs and the error, the linear weights ($\{\alpha_i\}_{i=1}^{n}$) norm, the number of neurons, and the RMSE in the validation set, respectively. The values in bold indicate that the goal associated with the characteristic was fulfilled.

The best ARX structure was computed considering a scanning of 48 lags (na = 1,...,48, nb = 1,...,48) for each variable, and a null delay for the inputs (nk =0). This model presents a RMSE in the validation set of 0.0253, and a maximum absolute error of 2.1 ºC.

Discussion

From the analysis of Table 2 it is possible to realise that the MOGA selects few lags of I_m (intensity) and many lags of T (temperature). The input T(k-1) appears in all preferable RBFNN, demonstrating the high dependency of the actual temperature on the temperature in the past 10 seconds. This fact indicates that the MOGA converges to a set of models with a physical meaning. The temperature 6 samples in the past (T(k-6)), that is 1 minute in the past appears with an absolute frequency of 9, disclosing its importance. The medium lags (between 20 and 40) appear with some frequency, in special the lags 20 and 35 with an absolute frequency of 6 and 5, respectively. The dependence of T(k) on the higher lags of the temperature is also visible. This affirmation is based on the appearance of lags with values between 39 and 47. The MOGA selection of medium and higher lags is probably due to the thermal capacity of the glycerine tank. However, MOGA indicates that T(k) is dependent on the actual intensity value (I_m(k)), and in the intensity 32 samples in the past (I_m(k-32)). The presence of few lags of I_m, and the presence of many lags of T can be related with the application of a constant intensity in the 60 minutes of heating, and the reduction of the intensity to zero between 60 and approximately 110 minutes, that is the dynamics of the system is completely dependent on the past values of the temperature.

From the analysis of Table 3 it is possible to realise that model 11 fulfils 2 out of 3 goals (test RMSE less than 0.003 and R_{ue} less than CI = 0.1) defined in MOGA.

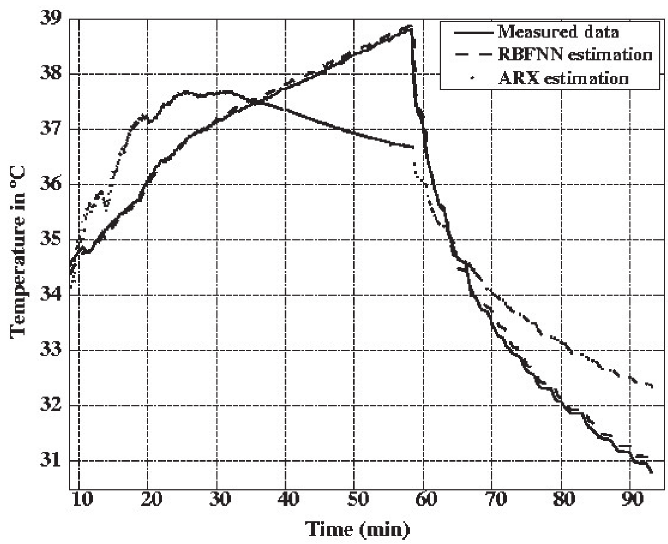

Figure 2: Estimated output by the model 11, estimated output by the best ARX, and the measured output (validation data).

This model has also a reduced number of neurons and presents the smallest RMSE in the validation set, being in this way considered the best-performed model. The maximum absolute error for this model is 0.2 ºC. The temperature estimated by this model and estimated by the best ARX model are presented in Figure 2, as well as the measured temperature at 2 Watt/cm^2.

In the preferable set there are also models (1, 2, 4, 6, 7, and 9) that fulfil one or none of the goals defined, but those that are not fulfilled are close to the desired values, and these models are also considered good models. A common characteristic of these models is the smallest number of neurons, showing that the estimation of T(k) in a glycerine medium is well performed with a small model (reduced complexity). The remaining models (3, 5, 8, and 10) present higher values for the RMSE in the validation set, showing a bad generalization capacity. All of these models present a high number of neurons, which can be explained by the MOGA attempt to fulfil the goals defined for R_{ee} and R_{ue}. Models with a high number of neurons tend to model the noise of the inputs, decreasing R_{ee} and R_{ue} values. For example the model number 3 has 15 neurons (maximum value defined), fulfilling the goals defined for R_{ee} and R_{ue}, but presents a high RMSE in the test and validation sets.

Comparing the RMSE in the validation set obtained with the two strategies and observing Figure 2, it can be stated that the modelling of the temperature dynamics can only be attained with success using non-linear procedures, such as the RBFNN. The increase in performance obtained, justifies the computational time spend in the selection of the best RBFNN structures.

Conclusion

This paper presents a preliminary study of the neural networks applicability in temperature estimation in a homogeneous medium, having in mind the determination of safe conditions for the application of ultrasound therapies, such as the hyperthermia. The results reveal that this kind of modelling can be accomplished with success (maximum absolute error less than 0.2 ºC) using RBFNN models (non-linear modelling). The best RBFNN attains an increase in performance of one magnitude order than the best ARX model obtained. Despite the real data used in this work was collected in a in-*vitro* environment, the results point that the RBFNN is able to bring improvements to temperature estimation in biological tissues and eventually *in-vivo*, in real time.

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