A soft-computing approach for non-invasive temperature estimation

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EXTENDED ABSTRACT

The domain of thermal therapies applications can be improved with the development of accurate non-invasive time-spatial temperature models. These models should represent the non-linear tissue thermal behaviour and be capable of tracking temperature at both time-instant and spatial position. If such estimators exist then efficient controllers for the therapeutic instrumentation could be developed, and the desired safety and effectiveness reached.

In the past, several methodologies for non-invasive temperature estimation, based on electrical impedance tomography [1], microwave radiometry [2], magnetic resonance imaging (MRI) [3], and backscattered ultrasound (BSU) [4] were published. The sole methodologies that achieve the precision required for hyperthermia/diathermia (maximum absolute error inferior to 0.5 ^{o}C in 1 cm^3) are the ones based on MRI [4]. However, MRI is expensive and inadequate to use in some therapies. On the other hand, BSU brings some advantages: non-ionising behaviour, low cost, simple signal processing requirements, and the possibility of using the same form of energy for heating and for temperature estimation, if therapeutic ultrasound is used. Methods which use BSU, based on tracking parameters like temporal echo-shifts [5] and frequency-shifts [6] due to physical phenomena as medium expansion, and change in speed of sound, in wave attenuation [7], and on backscattered energy were published [4] with some limited success.

In this poster, the application of a soft-computing methodology for non-invasive temperature estimation by means of BSU is presented. The soft-computing approach involves radial basis functions neural networks (RBFNN) and multi-objective genetic algorithm (MOGA) [8]. MOGA is used to select the best-fitted RBFNN structures, trained with the Levenberg-Marquardt algorithm. Data were collected from a tissue-mimic phantom, heated by a therapeutic ultrasound (TUS) device working in continuous mode. Three different TUS intensities were applied (1.0, 1.5, and 2 W/cm^2). Backscattered ultrasound signals (RF-lines) were collected by an imaging ultrasound (IUS) transducer working in pulse-echo mode, placed perpendicularly to the TUS transducer. Temperature was collected in the points under study by three thermocouples, which were aligned along the IUS transducer axial direction and across the TUS transducer radial direction (1 cm spaced). At each 10 s, a RF-line and three temperature values were collect from the medium and transferred to personal computer via a GPIB bus. The TUS device heated the phantom during the first 15 min, then was turned off and the medium allowed to cool down to the surrounding room temperature in the next 15 min.The application of backscattered ultrasound (BSU) for temperature estimation depends on the extraction of at least one temperature-dependent feature from the RF-lines. In this work, the temporal echo-shifts were computed, showing a direct proportionality to the temperature, following the temperature increases and decreases in the medium. As three thermocouples were placed, then three echoes appear in each RF-line. Given that the study of the temperature evolution is to be performed independently at the points defined by each thermocouple location, then each echo was isolated using a rectangular window, and the temporal echo-shift computed for each one. The temporal echo-shifts were computed using an algorithm that directly evaluates continuous time-shift from sample data. This method constructs a spline-based, piecewise continuous representation of a reference signal (in this case the echoes in the first RF-line), then finds the minimum of the sum of the squared errors between the reference and the delayed signals to determine their relative time-shift [9]. Afterwards, the computed temporal echo-shifts and the measured temperature values were filtered and normalised to values between -0.5 and 0.5, and applied as neural network inputs.

After the MOGA execution, a set of 11 good individuals were obtained. These preferable individuals are the ones that fulfil or almost fulfil the a-priory defined goals. The preferable RBFNN temperature models were evaluated with data never used in the models, neither at the training or structural selection phases. In order to precisely evaluate the model generalisation performance these data included the nine possible operating situations, i.e. data collected at the three different intensities and from the three points. The best model presents a maximum absolute error less than 0.5 degrees Celsius (gold-standard value for hyperthermia/diathermia applications). It is worth mentioning that the best model presents low computational complexity enabling future real-time implementations.

Concluding, this work presents a soft-computing framework based on radial basis functions neural networks, for non-invasive spatial-temporal temperature estimation in a tissue mimic phantom. The best model presents a maximum absolute error inferior to the gold-standard value for hyperthermia/diathermia applications, showing a high generalisation capacity. Despite the attained precision, one of the important achievements of the proposed methodology is that both the models structure and parameters were extracted from the data, discarding mathematical simplifications and physical constant determination, usually employed in empirical modelling frameworks. For the near future it is planned to develop two and three dimensional models using the same approach, and include them in control models to supervise the therapeutic instrumentation activity.

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