Real-Time Non Subtraction Thermometry Using Artificial Neural Networks

M. Jayapalan[1]

[1]MR SW & Applications Engg, GE Healthcare, Bangalore, Karnataka, India

Introduction: Thermal monitoring in focused ultrasound applications is a crucial step where MR is most widely used as it provides better thermal monitoring capability than others. In MR guided focused ultrasound treatments (MRgFUS) regular PRF shift technique involves, some form of image subtraction using a baseline pre-treatment images. Subject motion and tissue deformation due to coagulation can severely distort these techniques. Self-referenced methods [1] require a large area of tissue around the ablation for polynomial fitting and can't be used when tissue cooling is applied to sensitive structures. Here a new method of thermal monitoring using Radial Basis Function Neural Network (RBFNN) trained by orthogonal least square algorithm [2] to estimate the phase value at any instant is proposed which is used as the baseline phase value at any instant in temperature measurement during sonications. This method eliminates the need for baseline subtraction and also tolerates subject-motion to a great extent.

Methods:

A feed forward, radial basis neural network is used as a surface function-approximator with two inputs, and a hidden layer as shown in figure 1.

Gaussian functions having minimal spread is used as kernel in each unit of hidden layer, While optimal number of units in hidden layer is obtained through orthogonal least square learning. Their centers are trained in such a way that the Gaussian functions best represents the phase information over the selected training surface. The surface co-ordinates (X, Y) of the selected region of interest, is used as input and their corresponding phase value as output for training. As shown in figure 2, a knee image is used in training; its phase information in the selected region of interest (region 1) is used for training the network. During training the orthogonal lest square algorithm determines the number of units in hidden layer and also their centers for a required level of network accuracy. On an average, for a training region of size 20 x 50 pixels and 99% required accuracy, the algorithm chooses 750 centers for the network.

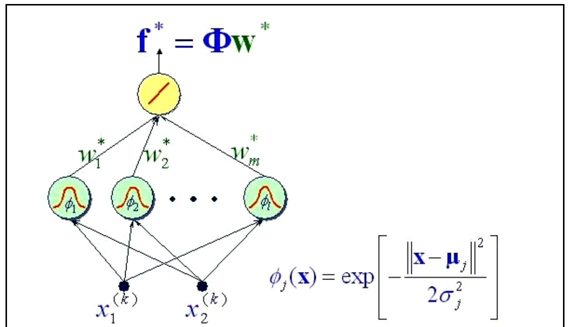

Figure 1. Network topology

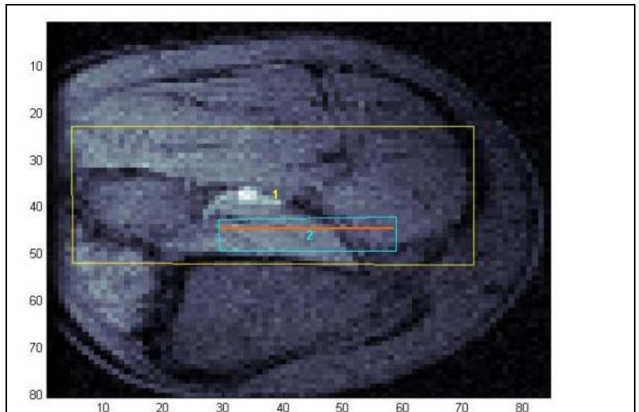

Figure 2. ROI selection for Training (1) and testing (2)

Results;

Region 2 of Figure 2 shows the region of interest used for testing the network. The actual phase value along the line (orange) with in the test region is compared with the network output as shown in figure 3. The blue line in figure 3, shows the actual phase values while the red one shows the phase obtained from neural network. It also proves that the trained network approximates the phase distribution of the image in that surface to the best possible degree. To monitor the temperature over a period of time, the phase information at any location obtained from this network is used as baseline and its difference with actual multiplied by a known constant [1] gives the temperature at that instant.

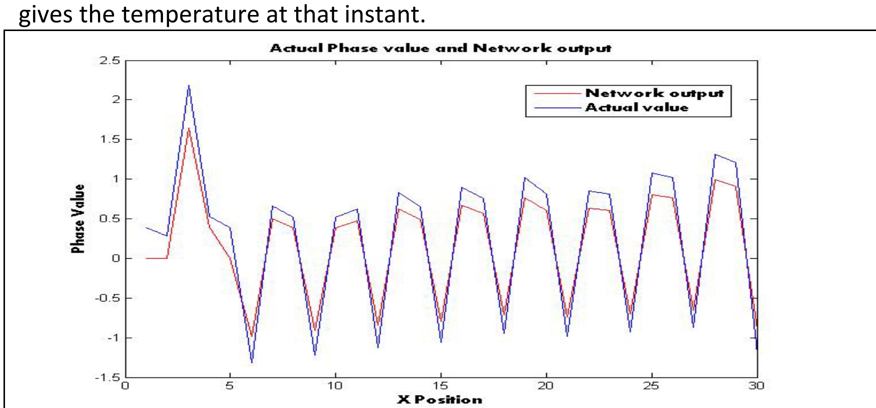

Figure 4. Phase value comparison from network output and actual value along a line with in a ROI shown in fig2

Discussions: Some of the advantages of this method are 1) unlike using the entire baseline images as in regular PRF thermometry, here the phase distribution along the surface is modeled using neural network of two inputs and is used whenever required. So resistance to patient motion is very high when compared with the later one. 2), This method needs training only once before the actual treatment, unlike modeling of background phase at every instant in referenceless thermometry which speeds up the measurement. So in clinical scenario, any missing phase information could be obtained in real time by feeding the corresponding locations (x,y co-ordinates) to neural network.

Reference: [1] Rieke V, Butts Pauly K. JMRI 27: 376-390 (2008) [2] Atul et.al., Physiological Measurement, 26:489-502 (2005)