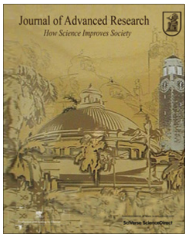
Journal of Advanced Research (2016) 7, 1045–1055

Cairo University

Journal of Advanced Research



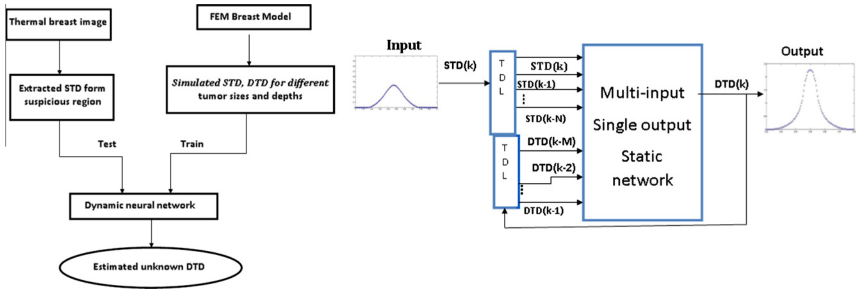
ORIGINAL ARTICLE

Parameter estimation of breast tumour using dynamic neural network from thermal pattern

Elham Saniei [a], **Saeed Setayeshi** [a,*], **Mohammad Esmaeil Akbari** [b], **Mitra Navid** [c]

[a] *Energy Engineering and Physics Faculty, Amirkabir University of Technology, Tehran, Iran*
[b] *Cancer Research Center, Shahid Beheshti University of Medical Sciences, Tehran, Iran*
[c] *Medical Thermography Dept., Fanavaran Madoon Ghermez Co. Ltd., Tehran, Iran*

GRAPHICAL ABSTRACT



Block diagram of the proposed model and Schema of applied dynamic neural network.

ARTICLE INFO

Article history:
Received 9 February 2016
Received in revised form 27 May 2016
Accepted 29 May 2016
Available online 3 June 2016

Keywords:
Breast tumour

ABSTRACT

This article presents a new approach for estimating the depth, size, and metabolic heat generation rate of a tumour. For this purpose, the surface temperature distribution of a breast thermal image and the dynamic neural network was used. The research consisted of two steps: forward and inverse. For the forward section, a finite element model was created. The Pennes bio-heat equation was solved to find surface and depth temperature distributions. Data from the analysis, then, were used to train the dynamic neural network model (DNN). Results from the DNN training/testing confirmed those of the finite element model. For the inverse section, the trained neural network was applied to estimate the depth temperature distribution (tumour position)

---

[*] Corresponding author at: Tel.: +98 (21) 64540.
E-mail address: setayesh@aut.ac.ir (S. Setayeshi).

Peer review under responsibility of Cairo University.

ELSEVIER Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.jare.2016.05.005

Neural network
Thermal pattern
Finite element model
Pennes bio-heat equation
Image

from the surface temperature profile, extracted from the thermal image. Finally, tumour parameters were obtained from the depth temperature distribution. Experimental findings (20 patients) were promising in terms of the model's potential for retrieving tumour parameters.

Introduction

Breast cancer is the most common type of cancer in the world and survival chances vary by stage at diagnosis [1]. In risk assessment of patients suspected of having breast cancer, thermography plays a key role. Breast thermography is a valuable method for cancer diagnosis in early stages of tumour growth, when it is not yet recognizable by mammography. Patients with an abnormal thermogram have a high risk of developing breast cancer during their lifetime [2,3]. Thermography is a physiological test while mammography is an anatomical one [3]. Thermovision techniques have been widely used to detect malignant breast tumours [4].

One basic question for breast thermography is how to quantify complex relationships between breast thermal patterns and underlying heat source parameters (size, depth and metabolic heat generation rate) [5]. Similar to other inverse problem applications, solving the breast thermography inverse problem is typically much more challenging, compared to its forward counterpart because of its intrinsically ill-posed nature.

Many researches have been conducted to understand relationships between surface thermal patterns and underlying physiological or pathological parameters. Analysing surface temperature and tissue temperature profiles, Ng and Sudharsan developed a 3-D direct numerical model of a breast with and without tumour [6,7]. They found that the tissue temperature profile was distorted at the tumour location, comparable well with *in vivo* tests. Mital and Pidaparti applied an evolutionary algorithm using artificial neural networks and Genetic Algorithms to estimate breast tumour parameters. Their algorithm was based on a simplified 2-D breast model and therefore, less practical for realistic data [8]. To estimate the metabolic heat generation rate of a tumour, Gonzalez performed a numerical simulation on the basis of the size and depth of the tumour achieved from X-ray mammography [9]. In more recent studies [8–10], an iterative optimization procedure based on forward thermography modelling techniques with spatial constraints, which requires a time-consuming computer calculation, is used to estimate tumour parameters. Also in most of the studies [6,7], the temperature distribution of body surface can be acquired as long as relevant data on the source of internal heat are known. However, in practice body surface temperature can be acquired through an infrared camera and the information of internal heat source should be approximated. This is an inverse problem.

The present study aimed to suggest a new solution to the inverse problem of breast thermography by using black box modelling. In order to address the inverse problem, surface temperature distribution, extracted from a breast thermal image and a dynamic neural network, was used. In order to validate the method, several cases with different tumour sizes and depths are presented. Fig. 1a shows block diagram of the proposed method.

Methodology

The proposed approach involved two steps. For the forward section, a finite element modelling was carried out. For this purpose, the Pennes bio-heat equation was solved to find the surface temperature distribution (STD) and depth temperature distribution at the tumour location (DTD). A 3D model of the breast similar to that of used by Ng and Sudharsan [6] was considered. Dynamic neural network was applied to map the relationship between the temperature profile over the breast model with the depth temperature profile at the tumour location. For the inverse section, the trained neural network was applied to estimate depth temperature distribution from surface temperature profile, extracted from a thermal image. Using this depth temperature distribution, the size and heat generation rate of the tumour were predicted via Eq. (1).

$$k\Delta T - bT = q_v rect\left(\pm\frac{a}{2}\right) \tag{1}$$

where T is the breast temperature distribution, a is the diameter of the heat source, $rect$ is the rectangular function, b is the perfusion term, k is the thermal conductivity and q_v can be regarded as the internal heat source. This equation is the 1-D static Pennes bio-heat equation. The dynamic bio-heat transfer process presented by Pennes is described in Eq. (2) as follows:

$$\rho c\frac{\partial T}{\partial t} = \nabla(k\cdot\nabla T) + W_b\cdot C_b\cdot\rho_b(T_b - T) + q_m \tag{2}$$

where ρ is density of the tissue, c is the heat capacity of the tissue, k is thermal conductivity of tissue and q_m is the metabolic heat term (or heat that the tumour generates from its metabolic processes). ω_b, c_b, ρ_b, and T_b represent blood perfusion rate, blood heat capacity, blood density, and arterial blood temperature, respectively [11]. At a steady state, time derivative is zero in Eq. (2) and to simplify the heat-transfer model in Eq. (1), the diffusion term b and internal heat source q_v were defined the same as in Eqs. (3) and (4).

$$b = w_b c_b \rho_b \tag{3}$$

$$q_v = w_b c_b \rho_b T_b + q_m \tag{4}$$

Analytical solution for the model is defined in the following equation:

$$T(x) = (T_{\max} - q_v/b)\cos h\left(\sqrt{\frac{b}{k}}x\right) + q_v/b \quad x \in \left[-\frac{a}{2}, \frac{a}{2}\right] \tag{5}$$

In the equations, $T(x)$ means temperature distribution function, x is the interval from the centre of the heat source to the point, and $T_{\max}$ is the maximum temperature. Eq. (5) shows the temperature distribution within the heat. To find coefficients of Eq. (5), assumptions (6) and (7) are considered, meaning that centre of the heat source has the maximum temperature.