Prediction of the Damage Coefficient in a Prostate Cancer Tissue during Laser Ablation Using Artificial Neural Networks

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***Abstract* – An attempt has been made to simulate the temperature distribution in prostate cancer tissue during laser ablation using finite element approach. Parameter studies have been carried out. The results have been consolidated using tool of artificial intelligence-Artificial Neural Network. Feed forward back propagation network has been used for this purpose. It has been found that artificial neural network is capable of predicting damage coefficient with a maximum error of 4%.**

Keywords–finite element analysis, laser ablation, matlab, neural networks, prostate cancer

I.INTRODUCTION

Prostate cancer remains a significant burden to society. Among the most common forms of the disease are cancer of the prostate and breast, accounting for 10 and 15% of all cancer related deaths in men and women, respectively. Current detection technology has led to a 5-year relative survival rate of greater than 90% for prostate and breast cancer. Traditional medical treatment of prostate cancer at its early stages, breast cancer, include radical prostatectomy, pelvic lymphadenectomy, lumpectomy and Mastectomy are major surgical procedures and are associated with many surgical complications. More men are being diagnosed with it at an early stage of their life. Focal therapy (FT) is emerging as an option because of its low risk. It avoids lifestyle-altering complications associated with radical treatment. Elevating the temperature of cancerous cells is known to increase their susceptibility to subsequent radiation or chemotherapy treatments. Higher intensity heat sources may be used to ablate the tissue in cases in which tumor exists in a well defined region. These facts are the basis for hyperthermia based cancer treatments. Of the many available modalities for delivering the heat source, the application of a laser heat source under the guidance of real-time treatment data has the potential to provide unprecedented control over the outcome of the treatment process. Ablation therapies delivered under various treatment modalities are a very promising, minimally invasive, alternative to standard treatment, and show significant potential as an effective cancer treatment to eradicate the disease while maintaining functionality of infected organs and minimizing complications and relapse. The physical basis for thermal therapies is that exposing cells to temperatures outside their natural environment for certain periods of time can damage and even destroy the cells. However, one of the limiting factors in all forms of ablation therapy, including cryotherapy, microwave, radio-frequency, and laser, is the ability to control the energy deposition to prevent damage to adjacent healthy tissue.

Neural network models attempt to simulate the information processing that occurs in the brain and are widely used in a variety of applications, including automated pattern recognition. The pattern recognition network uses the default Scaled Conjugate Gradient algorithm for training. At each training cycle, the training sequences are presented to the network. Each hidden unit transforms the signals received from the input layer by using a transfer function (sigmoid) to produce an output signal that is between 0 and 1, simulating the firing of a neuron. Weights are adjusted so that the error

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between the observed output from each unit and the desired output specified by the target matrix is minimized.

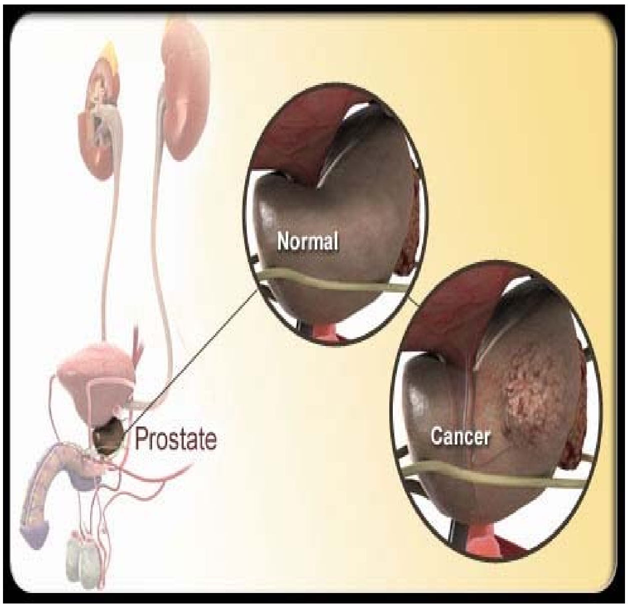

Fig 1. Prostate Cancer Tissue

II. INVESTIGATION AND ANALYSIS

In our analysis to determine the temperature distribution due to the incident lasers we adopted the MATLAB environment making use of the PDE tool box. An arbitrary simple circular domain of the prostate infected tumor was established. The number of lasers and their power (intensity) was fixed at 3 and 1500W respectively. The positioning of these lasers was then recorded in each case through the specification of their co-ordinates (x, y) in a 2-dimensional Cartesian system. The circular domain consisted of a circle of a fixed radius in each case. Once the laser positions were fixed, the necessary boundary conditions were imposed. Here in order to demarcate the tumor from the rest of the healthy tissue, body temperature conditions are applied along the periphery of the tumor. This is followed with the specification of the heat transfer 2-dimensional transient conduction equation i.e. the partial differential equation is of the parabolic type, whose coefficient are specified as depicted in the table below.

BOUNDARY CONDITIONS:

1) GENERALIZED NEUMANN FOR LASERS (CONSTANT HEAT FLUX-1500W/LASER).

2) DIRICHLET FOR TISSUE BOUNDARY (CONSTANT TEMPERATURE, 37 degree Celsius).

PDE SPECIFICATION:
PARABOLIC PDE (TRANSIENT CONDITIONS)

TABLE I

Properties of the prostate Tissue

Density	999 kg/m^3
Heat Capacity	4.2 J/ K
Thermal conductivity	0.552 W/m-K
Ablation temperature	50 deg Celsius

TABLE II

Properties of the lasers

Number of lasers(fixed)	Three
Laser Power(per laser)	1500watts

FEM analysis is then used to discretize the domain into several finitely sized triangles. Each triangle represents a 2-Dimensional element of the domain with fixed nodes. We set the mesh growth rate at a value of 1.9. For Transient conditions we apply a suitable heating time varying from 0 to 75 seconds in 5s intervals.

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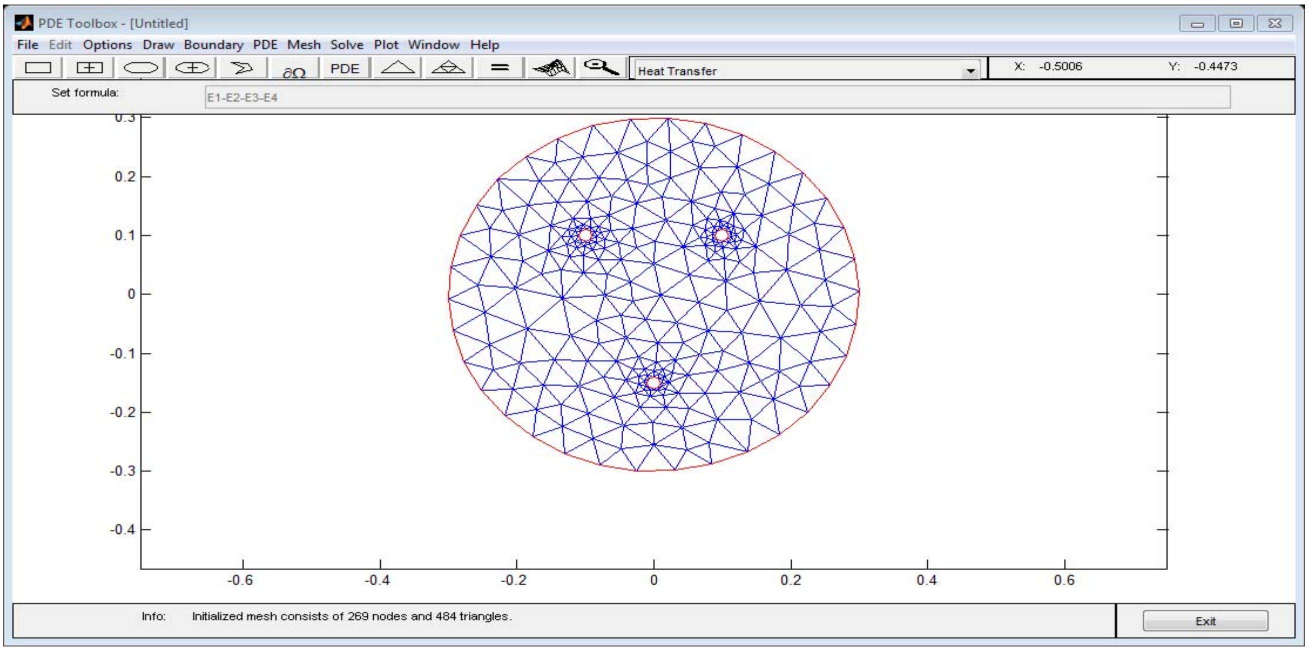

Fig 2. FEM mesh generation for tumor region

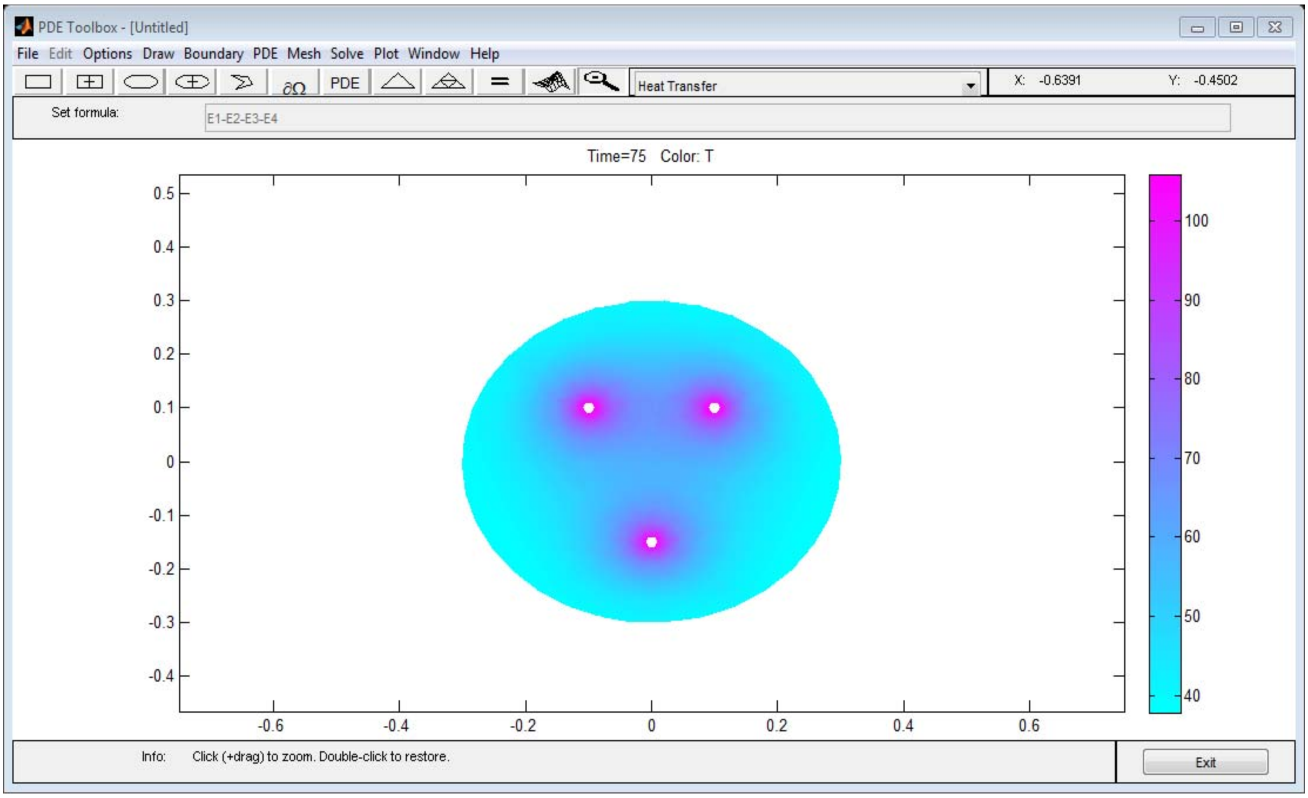

Fig 3. Snapshot of Temperature plot for a given set of laser coordinates

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Laser positions (coordinates) and heating time serve as input for neural network. FEM analysis gives nodal temperature values for given laser position for different time intervals. The number of nodes was found to vary from 230 to 270 depending on configuration. Temperature distribution for 230 different laser positions was obtained in intervals of 5s till 75s. The results obtained by FEM analysis was exported to MATLAB workspace. After this, DAMAGE COEFFICIENT was calculated.

Damage coefficient *may be thought of as the fraction of the total nodes in the domain maintained above ablation temperature of 50deg Celsius at any given heating time.*

At a temperature of 50 degree Celsius, ablation of human tissue takes place. As our aim is to predict the ablation caused by various laser configurations, damage coefficient was found to be more suitable as output than nodal temperatures as it directly gives us fraction of tumor which has been ablated.

For each configuration, for every time interval, the number of nodes having temperature greater than 50 degree Celsius was calculated. This way, a 1x230 damage coefficient matrix was obtained which would serve as target for neural network.

III. Network Formulation and Enhancement

TABLE III

Network Based data

Variable Parameters	Laser positions and Heating time
Training Algorithm	Scaled Conjugate Gradient
No of hidden Layers	Two
No of neurons/layer	20

Once a substantial amount of data has been put together by collecting temperature plots for 230 different configurations of laser positions we assemble all the data into a neural network. The network consists of an input and a corresponding output matrix relating to each of the input vectors respectively. We then make use of a pattern recognition tool in the MATLAB environment to translate the above vectors into a network. The network is then trained under default specifications. Some factual data about the network include:

1) NETWORK TYPE: 2 LAYER FEED FORWARD BACKPROPAGATION NETWORK

2) TRAINING FUNCTION: SCALED CONJUGATE GRADIENT BACKPROPAGATION

3) PERFORMANCE FUNCTION: MEAN SQUARE ERROR

4) TRANSFER FUNCTION: TAN SIGMOID

Variation of Number of layers and number of neurons give different outputs. Both these parameters have to be varied till outputs obtained are similar to targets.

- *The pattern recognition network uses the default Scaled Conjugate Gradient algorithm for training.*
- *Training vectors are restricted to 60% of the total number.*
- *The remaining 40% are validated and tested*
- *It utilizes a two-layer feed-forward network with sigmoid output neurons.*
- *The hidden layer has a set of 20 neurons to generalize the data sets.*
- *The number of neurons in each layer can be varied to obtain the highest efficiency of the network.*

Laser position and time interval (7x230) served as input for the matrix and damage coefficient (1x230) as target. For 2 hidden layers with 20 neurons each, following data was obtained on training.

EPOCH: 108

TIME: 16s

PERFORMANCE: 0.00233

GRADIENT: 0.00194

VALIDATION CHECKS: 6

These values represent the progress of training and final state once training is over.

Once the network formulation is completed we can simulate the same for any given data sets (input laser positions, heating time), and the network will simulate the expected damage coefficient. This is done using ‘sim’ function which causes specified simulink function/network to be executed for given inputs.

The simulated values of the damage coefficient were found to be sufficiently accurate indicating that the given network can be used to predict the ablation of the cancer cells caused for a given set of laser configurations and heating time.

IV. RESULTS

Once 230 datasets of the corresponding input and output matrices were gathered, the network was trained and subsequently simulated for input dataset to give the network outputs. The network was then simulated with datasets, which were within the range but outside input dataset, to check for its consistency. The results have been tabulated in the table provided. The error produced in finding the damage coefficient was found to be acceptable with sufficiently accurate results. Training set, performance plots were obtained.

TABLE IV

Damage Coefficient Table of results

Actual values: From FEM analysis

Predicted values: From ANN

Laser Coordinates	Heating Time	Actual	Predicted	Error %age
0.0086;0.1102;-0.065;0.053;0.086;-0.026	5	0.1957	0.1952	0.022
0.12;0.2; 0.15;-0.15; -0.2;0.1	50	0.413	0.425	-1.138
0;0.1275;0.085;-0.052;-0.086;-0.050	20	0.387	0.3771	0.88
0.05;0.1; 0.1;-0.1; -0.1;0.08	75	0.5956	0.5644	4.27
0;0;-0.08178;0;0.09397;0	35	0.4783	0.4792	-0.09
0;0;-0.0624;0.0655;0.08686;-0.01575	45	0.4913	0.512	-2.339
0;0;-0.092;-0.079;0.06;0.056	50	0.5435	0.5237	2.475
-0.001524;0.099;0.088;-0.05;-0.087;-0.047	60	0.5348	0.5286	0.7626
-0.070;0.070;0;-0.1021;0.088;0.046	65	0.5609	0.5358	3.23
0;0; -0.047;0.108; -0.097;-0.079	75	0.6133	0.5846	4.048

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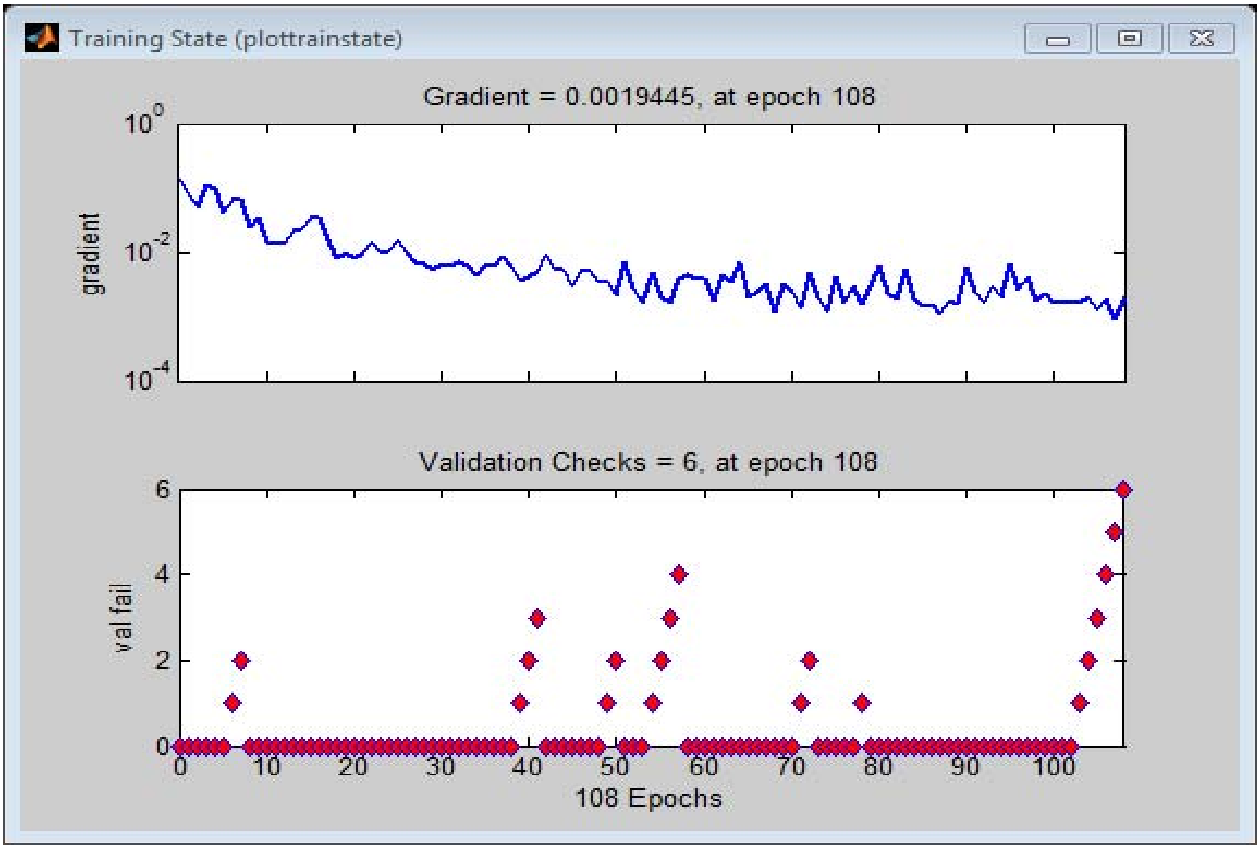

Fig 4. Training State Plot

V. CONCLUSION

Finite Element Method is used to predict the temperature distribution in a prostate cancer tissue during laser ablation. Laser position and heating time are used as a parameter in determining the temperature distribution. The results obtained from Finite Element Method have been consolidated using the tool of artificial intelligence –Artificial Neural Network in terms of damage coefficient. The maximum error in predicting the damage coefficient using Artificial Neural Network is found to be about 4%.

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