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Soft Tissue Modeling Using ANFIS for Training Diagnosis of Breast Cancer in Haptic Simulator

S. Amirkhani [a,*], A. Nahvi[b]

[a] Faculty of Mechanical Engineering, University of Guilan, Rasht, Iran
[b] Faculty of Mechanical Engineering, K. N. Toosi University of Technology, Tehran, Iran

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ABSTRACT

Soft tissue modeling for the creation of a haptic simulator for training medical skills has been the focus of many attempts up to now. In soft tissue modeling the most important parameter considered is its being real-time, as well as its accuracy and sensitivity. In this paper, ANFIS approach is used to present a nonlinear model for soft tissue. The required data for training the neuro-fuzzy model of soft tissue is provided from breast tissue numerical modeling in ANSYS 12.0 software. To validate the ANSYS mode, numerical data have been compared with the experimental data with an average error of less than 3%. On the other hand, for the validation of ANFIS model, testing session indicates a root mean square error of less than 0.02 (N), which shows the high degree of accuracy for the presented model. To evaluate the efficiency of this model, it has been used in the breast cancerous tumors diagnosis training haptic simulator. The presented model's real-time feature is about 100 times more than the maximum amount needed for force modeling simulations.

1. Introduction

Breast cancer develops from breast tissue. This cancer, after skin cancer, is the most common type of cancer among women. In many countries it is the second leading cause of cancer death in women [1].

Since an early detection of this cancer greatly increases the chance of an effective treatment, timely diagnosis of the cancer is of utmost importance to scientist [2]. So far various methods have been developed to detect the breast cancer [3]. One of the earliest ways of diagnosing the disease is self-examination. It is recommended that women self-examine themselves every month. Consequently, providing women with training services regarding examination will be significantly effective in early diagnosis of the disease. Thus, employing modern tools like force feedback simulations, not only provides an influential experience, but also will signify the importance of the issue to the trainees. First attempts to simulate with force feedback for medical skills training began from early 90s [4]. From the research perspective, many operations such as Laparoscopic, eye and bone surgeries are implemented in virtual environments [5, 6]. Also, some researchers have worked on breast cancer palpation training. In their project, augmented reality (AR) technology was used for haptic simulation in breast cancer palpation [7]. In addition, Solanki et al. have presented a haptic simulator for breast cancer diagnosis. In their work, a mass spring model is used as tissue [8].

In every haptic simulator, the user interacts with the virtual environment using touch and sight senses. Therefore, both should be real-time to fulfill the sense of reality in the user. In order to have a real time image, 30 Hz updating rate would be sufficient. However, for a real time force feedback, the haptic force needs a more than

* Corresponding address: University of Guilan, Rasht, Iran.
E-mail address: Amirkhani_saeed@yahoo.com.

300 time update rate per second. Therefore, computational time has a greater importance in force modeling. Common methods used for soft tissue modeling include methods that are based on differential equations and finite element methods [9, 10, 11, and 12]. Both methods have their disadvantages. For example, the method based on differential equations needs physical parameters of the object and defining these parameters is difficult. Even if we have their values, they include difficult nonlinear equations which make the work challenging. Also, finite element method is usually time-consuming and, therefore, impossible to be applied in real time haptic simulator in models with numerous elements and high precision.

So far, numerous attempts have been made to develop a real-time soft tissue modeling; for instance Niroomandi and et al. presented a technique able to deal with geometrically nonlinear models, based on the employment of model reduction techniques, along with an efficient non-linear solver. This technique is based on the construction of a complete model using finite element modeling or other numerical techniques and the extraction and storage of the most relevant information in order to construct a model with very low degrees of freedom, but that takes into account the highly non-linear response of most living tissues [13].

Courtecuisse et al. presented a numerical method for interactive real-time simulations, which considerably improves the accuracy of the response of heterogeneous soft-tissue models undergoing contact, cutting or other topological changes [14]. González et al. introduced a strategy for the real-time simulation of contact between nonlinear deformable solids at haptic feedback rates. The proposed method is somehow related to the Voxmap Pointshell method for two deformable solids [15].

In this paper, adaptive neuro fuzzy inference system (ANFIS) method is used for breast tissue modeling. For the first time in 2006, neuro-fuzzy model was used for modeling soft tissue cutting in surgery simulation [16]. They used a two-input single-output TSK system for surgical cutting force model, in which cutting depth and cutting velocity are inputs and cutting force is output. However, the present work discusses the breast palpation force model, which is more complex than surgical cutting model.

The three coordinates of the palpation place and the penetration depth are the four inputs of the model and the three force components are the model's outputs. The proposed neuro-fuzzy model is very fast, making it a suitable force model for haptic simulation. Since in the neuro-fuzzy method only the proper data related to the tissue is needed for identifying and implementing the model, the data could be provided using numerical modeling or laboratory experiments. Accordingly, the rest of the paper is organized as follows. First, the haptic interaction of simulator is briefly reviewed. Then, the ANFIS structure of the proposed model is explained. The next section discusses the data provision method for soft tissue. After that, the training method for modeling soft tissue, and its application in the simulator, is presented. Finally, the last section is dedicated to the concluding remarks.

2. Haptic Interaction

The basic elements of a haptic simulation system include user, force and motion interface of virtual environment [17]. Force interface, in fact, makes the force and motion connection between the user and virtual environment and the images are displayed to the user using graphic interface. The connection between virtual environment and force and graphic interfaces is real time [18]. In the connection circuit of virtual environment and haptic interface, called haptic control circuit, position, and sometimes applied force, is observed. Then, the appropriate force is calculated using the force model, and is sent to the haptic interface. Also, using the connection between virtual environment and graphic interface, the graphic model is synchronized and the changes in the model in virtual environment are displayed to the user [19]. Force circuit usually runs at 300-1000 Hz, while graphic rendering (because human eyes cannot detect inconsistency of the images shown above 50 Hz) is slower and runs approximately at 30-50 Hz. Reduction in the frequency of haptic circuit causes problems such as hand trembling, force inconsistency, and even instability and, therefore, reduces the quality of force produced by haptic interface. In figure 1, the basic elements of haptic simulation and their interaction are shown [20]. In the cancer diagnosis simulator, the user takes the haptic end effector and using the images shown on graphic interface approaches the virtual object and touches it. In figure 2, the connection in the haptic simulator for simulating breast cancer diagnosis is shown. In force generating algorithm, the first step is detection of contact with the virtual object.

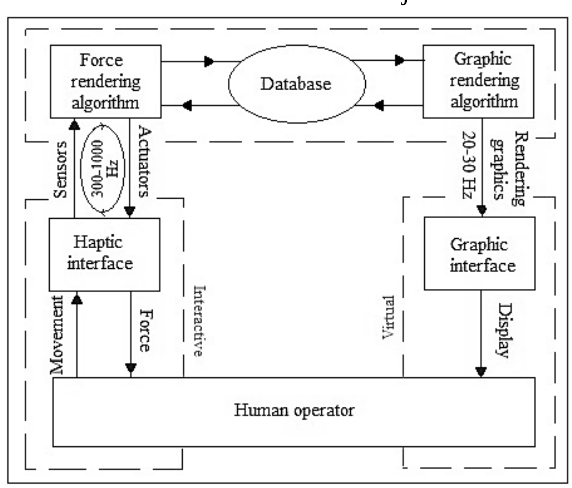

Figure 1. Basic elements of haptic simulation and their interaction [20]

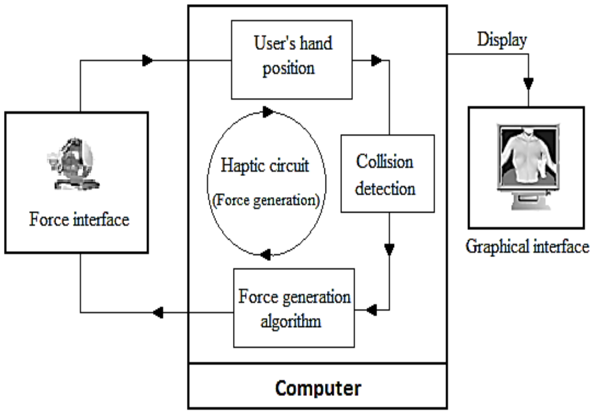

Figure 2. Simulator's haptic circuit

The reason is that the force applied to the hand of the user before the contact equals zero, and after the contact, depending on the depth of penetration in the virtual object, the tissue force model calculates the appropriate force. The obtained force is conveyed to the hand of the user using the haptic interface operators.

In order to detect the contact and calculate the depth of penetration for the last operator of haptic interface, firstly, the closest triangular mesh of the surface of virtual object to the haptic point (end effector) should be identified. This can be calculated by comparing the distances between mesh centers and the haptic point [21]. Then, it should be understood whether the haptic point is positioned over the mesh or not. For this purpose, Barycentric coordinates are used. According to figure 3, the condition whether the haptic point is positioned over the mesh can be achieved as follows

$$U = \frac{\overrightarrow{AP}.\overrightarrow{AB}}{|AB|} \quad ; \quad V = \frac{\overrightarrow{AP}.\overrightarrow{AC}}{|AC|} \qquad (1)$$

If (U&V > 0) and (U+V < 1), then P is inside the mesh [22].

After this step, in order to inspect if the haptic point is inside the virtual object or outside it, the gradient direction is used. If the end effector of the robot is not inside the virtual object, the force applied to the user's hand will equal zero. On the other hand, if it has penetrated into the virtual object, appropriate force will be calculated according to the depth of penetration using soft tissue force model and will be conveyed to the user's hand by interactive operators.

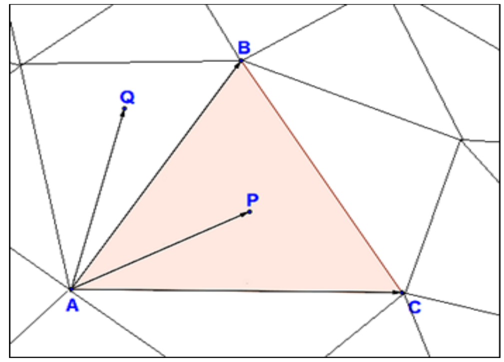

Figure 3. A part of virtual object's surface mesh

The soft tissue force model presented here has four inputs and three outputs. Three of the four inputs include (x, y, z) properties of the contact point of the end effector with the virtual object's surface before the change in its shape. The fourth input is the depth of penetration in the perpendicular direction to the body which is obtained during the detection of the contact between the haptic point and virtual object. The model's output includes three force parameters.

Since Sugeno fuzzy systems have one output, in this work, three four-input one-output Fuzzy systems are used. In Figure 4 the related control diagram is shown.

3. Soft tissue modeling

3.1. ANFIS structure of the model

By combining the fuzzy systems and the neural networks, a powerful tool is achieved which both benefits the training characteristics of the neural networks and has a performance equal to an inference fuzzy model.

The neuro-fuzzy system corresponds to a fuzzy model of Takagi-Sugeno, in which the weights of the neural network are equivalent to the parameters of fuzzy system [23]. This structure was first presented by Jang in 1993 [24].

ANFIS structure contains five layers of the feed forward neural network as the fuzzification layer, the rule layer, the normalization layer, the defuzzification layer and a single summation neuron where the nodes of each layer behave similarly.

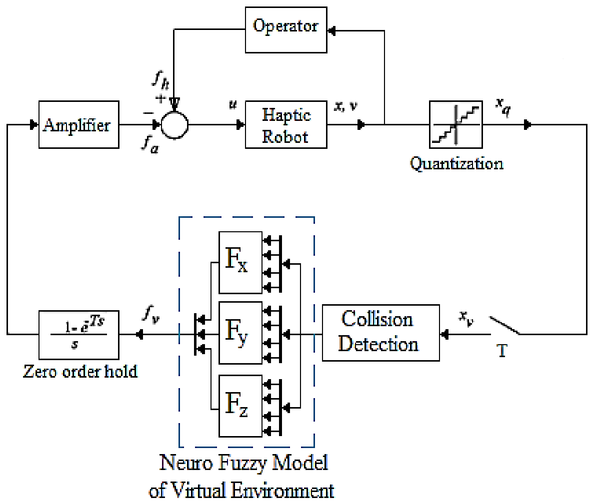

Figure 4. Block diagram for the control circuit

Soft tissue model is a 4-input single output model whose optimum number and type of the membership function will be determined in the identification section. Fuzzy system rules would be as

R_i : if x_1 is A_1 and x_2 is B_1 and ... then

$$y_i = p_{0i} + p_{1i}x_1 + p_{2i}x_2 + p_{3i}x_3 + p_{4i}x_4 \qquad (2)$$

In ANFIS method, the total number of fuzzy rules is dependent on the number of membership functions. A_i and Bi are fuzzy sets and y_i is the output within the fuzzy region specified by the fuzzy rule. p_{0i}, p_{1i}, p_{2i}, p_{3i} and p_{4i} are the design parameters which are determined during the training process. Every node in the first layer is a fuzzy set and any output of any node in this layer corresponds to the membership degree of input variable in this fuzzy set. In this study, the triangular-shaped membership function is employed. For a triangular-shaped membership function, μ_i is given as

$$\mu_{Ai}(\mathrm{x}) = \max(\min(\frac{x-a_i}{b_i-a_i}, \frac{c_i-x}{c_i-b_i}),0) \qquad (3)$$

Where x is value of input i node, and a_i, b_i and c_i are the parameters of membership function of this set. In the second layer, every node computes the degree of activation of any rule. Membership functions are then multiplied in this layer.

$$w_i = \mu_{Ai}(x_1)\,.\,\mu_{Bi}(x_2)\,.\,\mu_{Ci}(x_3)\,.\,\mu_{Di}(x_4) \qquad (4)$$

In the third layer, the ratio of the activity degree of i rule to the sum of activation degrees of all rules is calculated. Also, w_i is the normalized membership degree of i rule.

$$\bar{w}_i = \frac{w_i}{\sum_{i=1}^{n_{Rull}} w_i} \qquad (5)$$

Each node of the fourth layer is a comparative node that has an output as follows:

$$\bar{w}_i y_i = \bar{w}_i (p_{0i} + p_{1i}x_1 + p_{2i}x_2 + p_{3i}x_3 + p_{4i}x_4) \qquad (6)$$

The final output of network is y which is produced by the node of the fifth layer as a summation of all incoming signals.

$$y = \sum_{i=1}^{n_{Rull}} \bar{w}_i y_i = \frac{\sum_{i=1}^{n_{Rull}} w_i y_i}{\sum_{i=1}^{n_{Rull}} w_i} \qquad (7)$$

The training basis in ANFIS analysis is the back propagation method. In order to speed up the convergence rate, one can apply a hybrid method which is a combination of the back propagation and the least square solution. In the model training, the rules' parameters and the membership functions are modified in two steps. The schematic of the ANFIS model training is indicated in Figure 5.

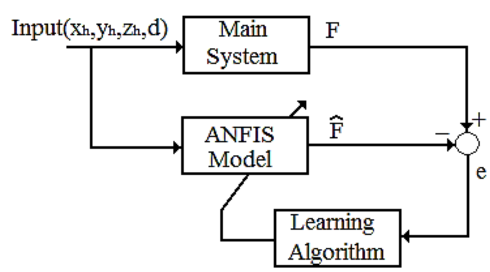

Figure 5. Schematic representation of ANFIS model training

3.2. Data provision

The data used for training of the ANFIS model is provided from tissue modeling in ANSYS finite element software. The mechanical properties of breast tissue and cancerous tumor used in the modeling are adopted from [25]. In their work, Krouskop et al. measured the mechanical properties of breast tissue and cancerous tumor and presented comprehensive data regarding them.

In numerical modeling, hyper elastic material is chosen. Also, for meshing, after checking different mesh types, triangular meshing was used. For validating the numerical results, the geometry of the sample used in [25] (experimental results are available) was modeled in ANSYS software. In Figure 6, the geometry of the loading is presented.

In this figure, D equals 30 *mm*. The results are obtained at seven displacement loadings and are compared to experimental data from [25] for both fat and glandular tissues. Therefore, the numerical results are validated with an average error of less than 3% to the experimental data (Figure 7).

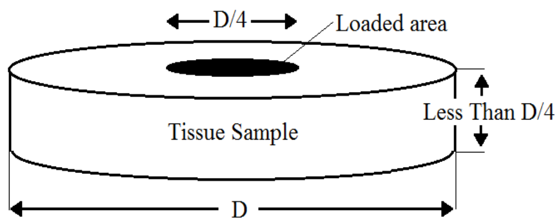

Figure 6. Geometry of loading

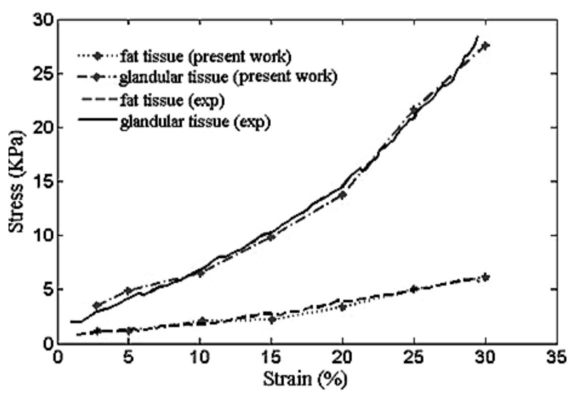

Figure 7. Numerical data for the current work compared to the experimental data from [25]

After validating the numerical model results, the geometry of glandular breast tissue, with the above-mentioned features, was entered into the software. After applying boundary conditions, in order to provide the needed data, displacement loading on the surface nodes was applied in the perpendicular direction to the body with five difference values (2, 5, 8, 12 and 16 *mm*). Since breast examination is done by palpating breast with two fingers and it has a contact area of 2 cm^2, probe diameter is set to be 1.6 *cm*. The loading process is presented in Figure 8. These loadings are applied to 153 points on the tissue, which were selected regularly. The intended number of points for loading, which covers nearly the entire surface the object in acceptable distances, seems to be adequate for the loading. Consequently, 765 values are obtained in total and for each value the amount of strain in the loading point is recorded. Figure 9 shows the distribution of loading points on the organ. To calculate force parameters, tensions are multiplied by an equal of two fingers' palpation area (2 cm^2). Figure 10 shows the tension values in x axis after loading a point (5 *mm* displacement).

3.3. Training the model

Steps to presenting a neuro-fuzzy model can be stated in three phases; data provision for the system, training model evaluation to choose the best structure for having the best model, and testing the model. In breast examination, what is expected from a soft tissue force model is to calculate the symmetric force when the tissue is palpated (displacement on the surface nodes).

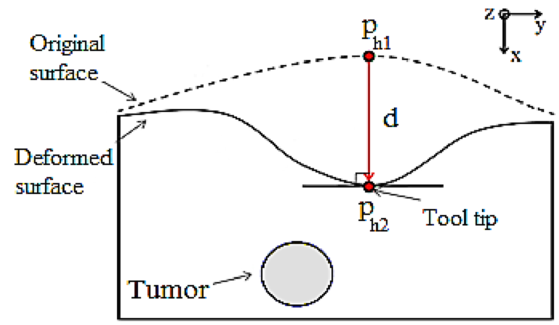

Figure 8. Schematic representation of loadings at five values (2, 5, 8, 12, 16 *mm*)

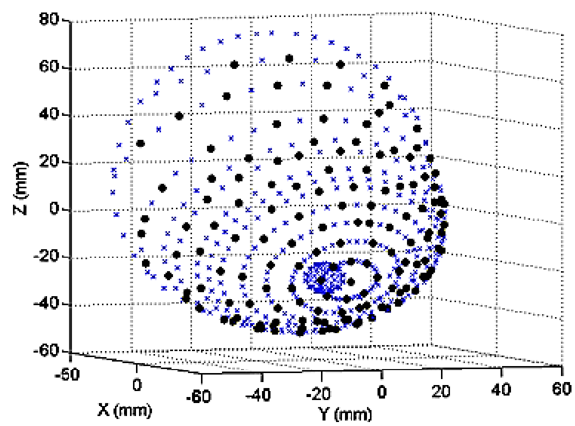

Figure 9. Loading points for data provision (filled points)

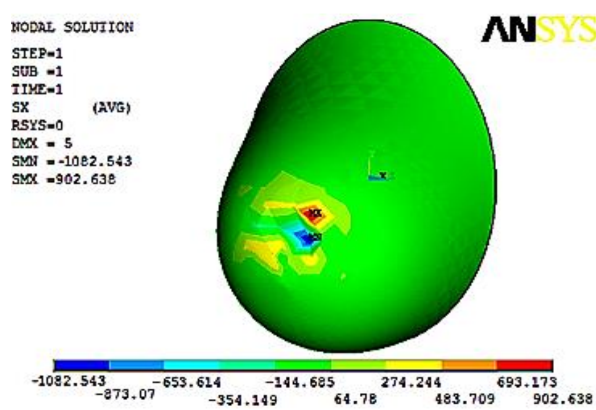

Figure 10. A sample loading in Ansys software (tension in x axis)

For the ease of data provision phase, displacement is always supposed to be in one direction, i.e. in the *x* axis. As a result, the model's inputs consist of three spatial load parameters and one compression (or displacement) parameter. The model's output would be three tissue feedback force parameters in the loading point. Since in ANFIS method the model could have only one output for three force parameters, three neuro-fuzzy models are presented. Each of the models is trained using 80% of the total amount of the data and tested and validated using the remaining 20 percent.

In training phase, twenty percent of the training data are used for evaluating the model to choose the best structure of the model. The data used here is different from the data used for testing (i.e. it is a part of the 80% training data) and will be used in the model training process after choosing the model structure. In this phase, the type of membership functions (and their number at every input), and the epoch for achieving the best model are chosen. As explained, all the steps were done and the best structure for every model was chosen. It should be mentioned that for model training, hybrid training algorithm is used. Root Mean Squared Error is used for estimating training error and testing error. The model parameters are shown in table.1

In Figure 11 the output values of neuro-fuzzy model for the test data are compared to real values. In this figure, the continuous line represents the real values of each force parameter and the dotted line represents ANFIS models' output. RMSE error values in the testing session equal 0.0791, 0.0066, and 0.0181 Newton for three models respectively. Therefore, it is verified that the neuro-fuzzy model's performance is very good.

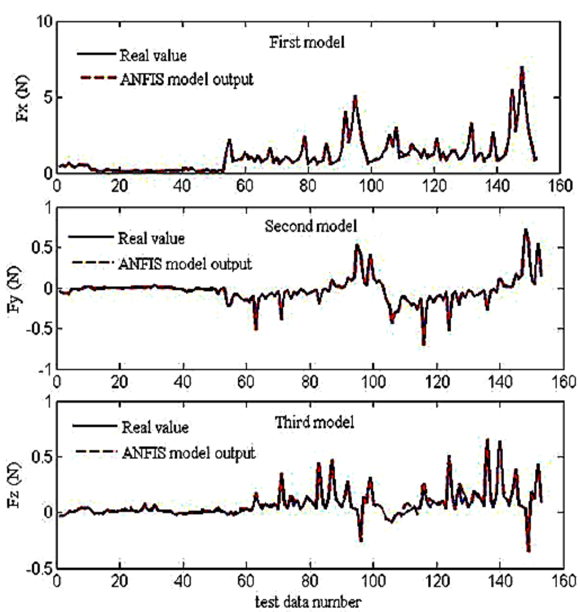

Figure 11. Comparison of neuro-fuzzy model's output values and real values

Table 1. Parameters of the proposed neuro- fuzzy model

Model parameters	Model 1	Model 2	Model 3
Output	Fx	Fy	Fz
Membership function	Triangular	Triangular	Triangular
FIS structure	3-3-3-2-54	4-4-4-2-128	4-4-4-2-128
Epoch	29	30	15
Training error	0.0318	0.0318	0.0043
Testing error	0.0791	0.0063	0.0181

4. Simulator implementation

Simulator implementation for cancerous tumor diagnosis is done in MATLAB software. For the simulator to be real-time, real-time toolboxes of MATLAB and S-Function block are used. Also, all time-consuming parts of the program like contact detection algorithms are coded in C and used as S-Function blocks in the program. Graphic modeling for the simulator is done in V-Realm Builder 2.0 which can be linked to MATLAB. This software is based on VRML, which is a virtual reality programming language. This language is similar to HTML and some call it three dimensional HTML. VRML is an interactive animating language. It should be mentioned that because of force modeling, graphic is not flexible in this language.

The haptic interface used in this work is called Falcon, which was produced by NOVINT incorporation in 2007. This device eliminated one of the limitations of using haptic devices which was related to their being expensive. According to the features of this interface, it can be used for haptic simulation. In figure 12, Falcon is displayed, and the properties of this haptic interface are presented in table 2.

Figure12. Novint Falcon haptic interface

Table 2. Properties of Falcon haptic interface

Property	Amount or type
Workspace	10*10*10 cm^3
Maximum force	10 N
Resolution	400 dpi
Control frequency	1000 Hz
Connection	USB 2.0
Weight	3 kg
Power	30 watt, 110 V

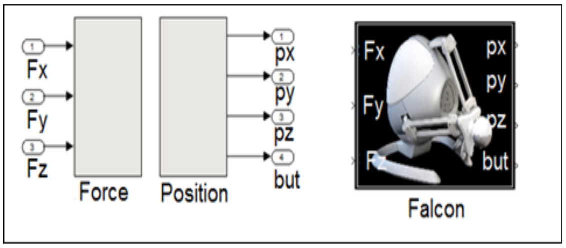

Figure 13. Falcon block

The Falcon device utilizes a USB interface connected to the computer and uses a 1 *kHz* update rate with commanded forces [26]. Delta robot configurations, with other characteristics of this interface, indicate that this interface would be suitable for use in our work. Data exchange between haptic robot and computer is done by receiving the position of final haptic operator using the codes of Software Development Kit (SDK) and sending them to Matlab using C commands. After this step, depending on the force model's output, the appropriate forces to be applied on the user's hand are calculated and sent again to C, which then, using SDK commands, are sent to haptic interfaces and using motors are conveyed to the user's hand. The block related to Falcon haptic interface is developed using modeling S-Function Build files in Simulink environment in Matlab software. A MEX file with mexw32 extension is usable for S-Function blocks. Haptic interface's block consists of two detached blocks, one of which receives the force and the other spots the situation. In figure 13, Falcon block is shown. In this figure the fourth output of the haptic interface's block is associated with a button which is placed on the end effector of the robot; and when the button is pushed the output equals 1 and when it is released it equals zero.

This button is used for disconnecting force simulation and adjusting the graphic camera. The simulation is run on a PC equipped with an Intel core 2 Quad 2.66 GHz

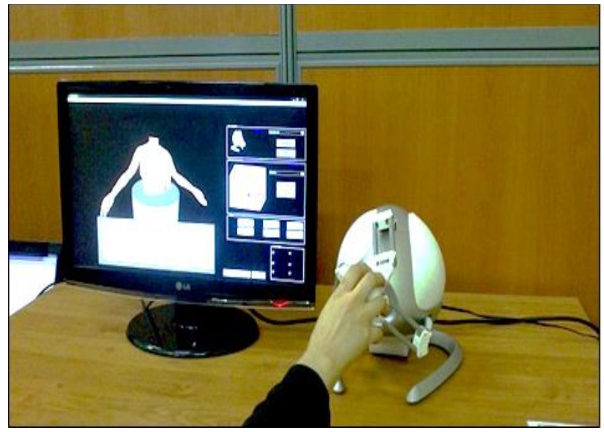

Figure 14. A user using the simulator

processor, a 2 GB RAM, an ATI Radeon 4350 graphic processor, and a Windows XP operating system. Figure 14 shows a user using the simulator. After the measurements it was observed that when the frequency of graphic interface is 30 Hz, the frequency of force cycle simulator equals 322 Hz.

Although the simulation is completed in Matlab software, the simulation is absolutely real-time. Concerning the neuro fuzzy model's speed, it should be mentioned that by the measurements done on the PC used for simulation, it was observed that the model is able to calculate the force for more than 10^5 inputs per every second. This means that, the processing load related to the model is 100 times smaller than the optimum value for the simulation.

5. Conclusion

In this paper, the approach of using intelligent methods to identify and model soft tissue was presented and positive results were achieved. High capability of neural network based methods such as ANFIS, in the identification of complex systems, as well as the high speed of the Sugeno fuzzy model, enables this method to be used for modeling complex systems such as soft tissue. It only needs proper data of the tissue, which can be provided by laboratory or numerical methods.

In this article, a neuro-fuzzy model for breast tissue containing cancerous tumor was presented and then implemented in a breast cancerous tumor diagnosis training simulator. The RMSE errors for the force model of cancerous breast tissue for the forces in *x*, *y*, and *z* axes, according to numerical data, were observed to be .0826, .0077, and .0209 Newton respectively. Also, it was observed that the presented force model can be synchronized for about 10^5 times every second.

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Biography

Saeed Amirkhani received the B.S. degree from Zanjan University, Iran, in 2010, the MSc. degree from K.N. Toosi University of Technology, Iran, in 2012. He is currently a PhD student at the Department of Mechanical Engineering, Guilan University. His research interests are virtual reality, haptic interfaces and system Identification.

Ali Nahvi received the PhD degree in mechanical engineering from the University of Utah in 2003. He is currently with the Faculty of Mechanical Engineering, K. N. Toosi University of Technology. He is the recipient of Anton Philips Paper Award in 1998. His research interests are virtual reality, especially design and control of driving simulators, educational simulators, and haptic interfaces.