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SIMULATION OF HEMODYNAMICS IN A GRAFT-TO-VEIN ANASTOMOSES BY ADAPTIVE NEURO-FUZZY BASED MODELING

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Abstract- A new methodology for simulating the flow field inside an arteriovenous (AV) graft to vein anastomoses by the adaptive neuro fuzzy inference system (ANFIS) is presented in this study. For determining the optimal AV graft angle, an ANFIS-based model of neuro fuzzy-graft-vein (NF-GVEIN) is proposed. Therefore engineering design of the graft can be supported. The advantage of this neuro-fuzzy hybrid model is that it does not require the model structure to be known a priori, in contrast to most of the modeling techniques. A case study with real experimental data was carried out. NF-GVEIN was optimized by means of selection of the algorithm among 34 ANFIS algorithms by terms of minimal error. The optimal neural network structure was determined. The optimal AV graft angle causing the least turbulence was obtained. The simulation results showed that this model is feasible for forecasting of finding the optimal AV graft angle inside AV graft to vein anastomoses with different flow rates.
Key Words: Neural Networks, ANFIS, Hemodynamics, Graft Design

1. INTRODUCTION

Extensive numerical [1, 2] and experimental [3, 4] investigations of the fluid dynamics of distal end to side anastomoses associated with arterial bypass grafts have been conducted, motivated by the fact that this junction is a site of particularly high risk in the formation of intimal hyperplasia and other forms of arterial disease. This junction offers a situation providing a complex mix of fluid dynamic phenomena and can potentially aid the quest for causal linkages between disease localization and fluid dynamics details for arteries. Similar geometries occur at the downstream end of an AV anastomosis created by incorporation of a loop of graft material, polytetrafluroethylene (PTFE) or Teflon, for the purposes of repeated high flow rate vascular access, as in renal dialysis. Similar experiences of intimal hyperplasia leading to loss of patency, but now in the vein rather than the downstream artery, have as in the arterial bypass graft situation led surgeons to experiment with a variety of detailed geometric designs when forming the end to side anastomosis between the graft and the vein. Kanterman [5] showed that hyperplastic stenoses occur predominantly at the proximal venous segment (PVS), downstream of the AV graft to vein connection, as shown in Figure 1 (a, b), [8, 9]. This suggests the possible involvement of disturbances created in the graft-to-vein junction and advected downstream. To date there has been a few detailed set of investigations [6] of the fluid dynamics of the AV graft to vein anastomosis. Shu [6] obtained the mean velocity profiles and wall shear stress (WSS) inside realistic AV graft models. They implicated the low and oscillating WSS near the stagnation point and separation region in the development of a lesion distal to the toe. No measurements of turbulence levels were reported. The first modeling study was done on the turbulence measurements quantitatively under the steady and unsteady flow conditions [7, 8, and 9]. They tried to understand the location of the wall shear stresses and turbulence regions inside an AV graft to vein anastomoses model. The modeling techniques [1, 3, 4, and 9] did not use neural networks and fuzzy logic.

The neuro fuzzy models used by Hasiloglu [10], Nikov and Stoeva [11] are very appropriate for computational modeling of the non-linear dependencies. There is a non-linear dependence between flow velocities and flow parameters, such as graft angle, flow rates and measurement coordinates. Neuro fuzzy approaches can help to create a non-linear model of the flow field inside the graft to vein anastomoses and determine the optimal graft to vein angle which will lead the better graft designs. Due to high flexibility of adaptive networks, the adaptive neuro fuzzy inference system (ANFIS) [12, 13] was selected among neuro fuzzy models to model the flow field inside a graft to vein anastomoses under steady flow conditions.

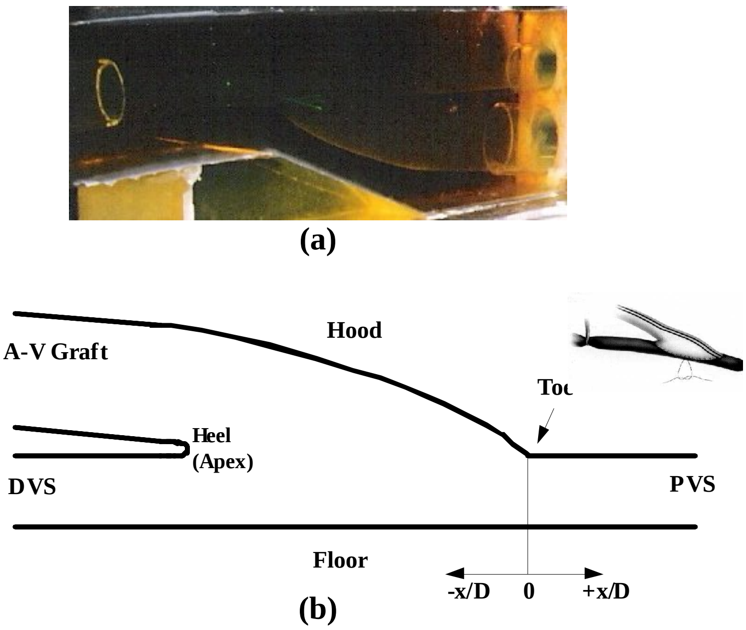

Figure 1. (a) 3D view, (b) bifurcation plane geometry and nomenclature of the AV graft to vein connection model

2. DESCRIPTION OF DESIGN METHODOLOGY

We are proposing a methodology NF-GVEIN for designing the best application conditions for the values of the AV graft angle α in the graft to vein anastomoses. Figure 2 shows the steps for determining the optimal α. At the first step the experimental data is collected. At the second step the obtained data is preprocessed. Then the model inputs and output values are defined. At the third step a fuzzy inference system (FIS) using the framework of adaptive neural networks ANFIS [13] is employed. The basic structure of a FIS consists of three conceptual components: a rule base, which contains selected fuzzy rules, a data base, which defines the membership functions (MF) used in the fuzzy rules and a reasoning mechanism, which performs the inference procedure upon the rules to derive an output.

FIS implements a nonlinear mapping from its input space to the output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping. The parameters of the if-then rules define a fuzzy region of the input space, and the output parameters. The rule structure of a FIS makes it possible to incorporate human expertise about the system being modeled directly into the modeling process to decide on the relevant inputs, number of MFs for each input and the corresponding numerical data for parameter estimation. In the present study, the concept of the adaptive network, which is a generalization of the common backpropagation neural network, is employed to tackle the parameter identification problem in a FIS. The last step of the NF-GVEIN methodology is the design of AV graft with optimal α value.

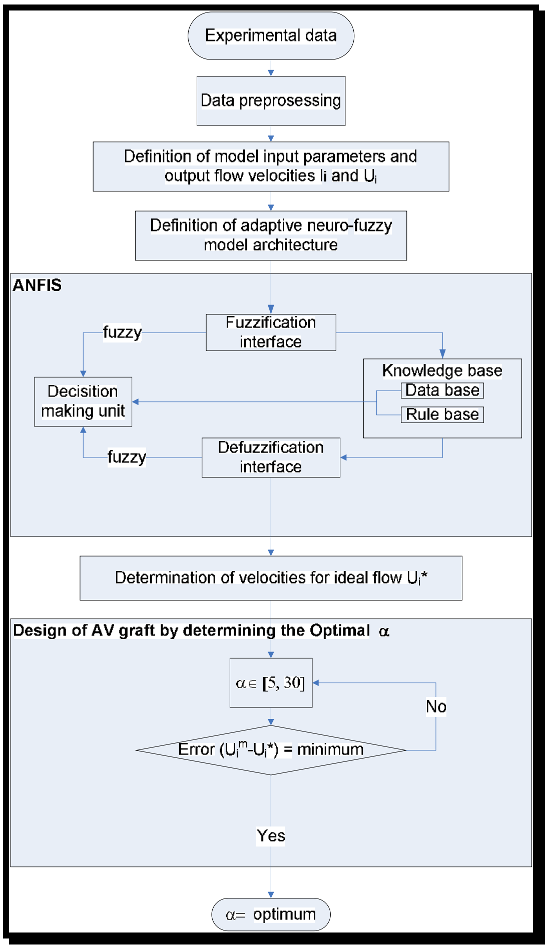

Figure 2. NF-GVEIN steps for designing of AV Graft

The fuzzy inference system maps input characteristics to input membership functions, input membership function to rules, rules to a set of output characteristics, output characteristics to output membership functions, and the output membership function to a single-valued output or a decision associated with the output. An example structure of the ANFIS is presented in Figure 3. Selection of the FIS is the major concern when designing an ANFIS to model a specific target system. There are various types of FIS characterized by their consequent parameters [10, 14]. The current study uses the Sugeno type fuzzy model since the consequent part of this FIS is a linear equation and the parameters can be estimated by a simple least squares error method. The shape of the membership functions depends on the parameters.

A typical fuzzy logic system consists of four major components: fuzzification interface, fuzzy rule base, fuzzy inference engine and defuzzification interface. The fuzzification interface (fuzzifier) converts numerical input data into suitable linguistic terms, which may be viewed as labels of the fuzzy sets. A fuzzy rule represents a fuzzy relation between two fuzzy sets. It takes form such as “If X is A then Y is B”. Each fuzzy set is characterized by appropriate membership functions that map each element to a membership value between 0 and 1. A fuzzy rule base contains a set of fuzzy rules, where each rule may have multiple inputs and multiple outputs. Fuzzy inference can be realized by using a series of fuzzy operations. The defuzzification interface (defuzzifier) combines and converts linguistic conclusions (fuzzy membership functions) into crisp numerical outputs. The basic ANFIS takes either fuzzy inputs or crisp inputs, but the overall outputs are fuzzy sets. The crisp output is generally obtained using different defuzzification strategies [13]. It amalgamates two procedures, the logic decision and defuzzification procedures into one composite procedure.

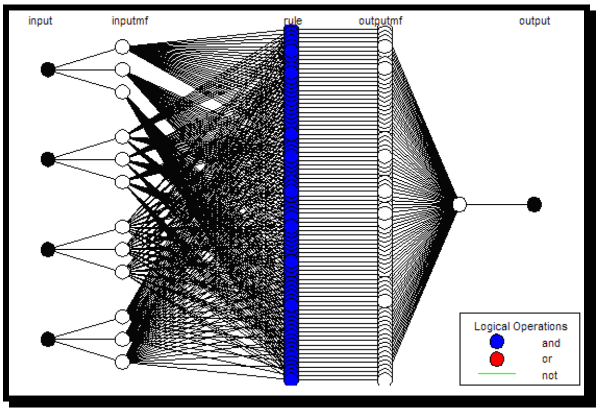

Figure 3. Optimal neural network structure for NF-GVEIN Model

3. CASE STUDY

For illustrating the NF-GVEIN methodology a case study with experimental data shown in Figure 4 was carried out, [8, 9]. This figure shows the velocity profiles inside the AV graft-to-vein connection using an in vitro modeling system used laser Doppler anemometer (LDA). The horizontal axis presents the location for the in vitro model and the vertical axis shows the velocity values which characterize the flow field inside this model.

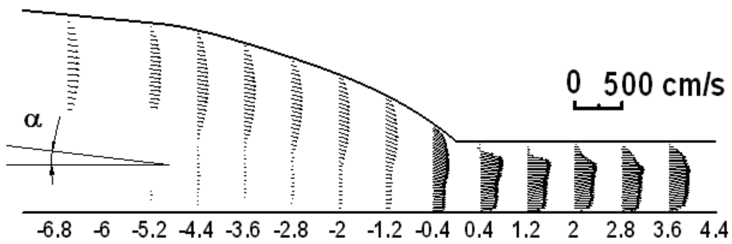

Figure 4. Velocity profiles of blood stream flow in graft-to-vein connection

Four input parameters and one output parameter were defined, Table 1. They are essential for accurate modeling of the flow field inside an AV graft-to-vein connection data. Two dimensional spaces (2D) was considered, X and Y were the measurements locations in the bifurcation plane of the in vitro model (Figure 4). The arteriovenous graft angle was specified as α and the flow rate for the steady flow conditions were given as inputs. As output parameter blood stream velocities (U_i) for 2D measurements were calculated from the instantaneous measurements Table 1. DVS is denoted as the distal vein segment and by x/D the non-dimensional coordinate system.

Table 1. Parameters of NF-GVEIN Model

PARAMETERS	**DIMENSIONS**
Input Parameters	
1. Measurement location X	mm
2. Measurement location Y	mm
3. Graft angle α	degrees
4. Flow rate	mm^3/s
Output Parameters	
1 Velocity $U_i = \sqrt{u_x^2 + v_y^2}$	cm/s

3.1. Experimental Data Collection

Velocity profiles were measured as millimeter-spaced points along the bifurcation plane of the in vitro model of AV graft to vein connection. At the Reynolds number Re = 1060, thirteen axial locations along the vein axis were examined, starting distally (upstream, DVS) at $x = -6.8D$ relative to the toe position, and extending proximally to $x = +3.6D$. Measurements revealed that the turbulent fluctuation amplitudes within the anastomotic region were comparable to or lower than those measured at the graft inlet ($x = -6.8D$). Based on the velocity measured in the sample volume of the Doppler ultrasound (V = 0.69 m/s), inlet diameter of the AV graft (D = 6mm), blood density (ρ = 1.05 g/ml) and assuming normal blood viscosity (μ = 3.5 mPa s), the above measurements lead to a Reynolds number ($Re_{in\ vivo} = \rho VD/\mu$) of 1060 for the patient shown in Figure 4. Then using dynamic similarity ($Re_{in\ vivo} = Re_{in\ vitro}$) the velocity (or flow rate) inside the in vitro model was found and used during in vitro experiments.

3.2. Definition of Fully Developed Turbulent Velocity Profile

For fully developed turbulent flows, the velocity profile [15] may be expressed as $V_{turb} = V_{max}(1\text{-}r/r_{tube})^{(1/m)}$ away from the laminar sublayer near the wall, where m ~ 7 for a wide range of Reynolds numbers.

3.3. Optimization of NF-GVEIN

For optimization of NF-GVEIN methodology the ANFIS algorithm with the lowest training error was selected, the optimal neural network structure was constructed and the optimal AV graft angle was determined. The performances of several ANFIS algorithms were determined using different MF types (trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, psigmf) and iterating different number of MFs from 2 to 10 (neurons); this selection procedure of a best algorithm for a data set is described by Karaca et al. [16]. ANFIS applies two techniques in updating parameters. For premise parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method to identify them. This approach is thus called hybrid learning method since it combines gradient descent and the least-squares method. According to their training error the best algorithm for the modeling of the flow field inside graft to vein anastomoses is the *generalized bell* membership function (gbellmf) which has linear MFs with hybrid optimization method. The best performances for each of the MFs were generally obtained with 3-5 neurons (number of MFs employed) with regard to the difference in values of training and validation errors. As a result, the optimum number of MFs for gbellmf was determined to be 3 with the mean squared error value of 0.15 (Figure 3).

As validation data set, the same input values of training data set were used. The output value of the validation data set was obtained from the fully developed turbulent velocity profile for each measurement line (Section 3.2). For the training data set, the squared mean error decreases while the neuron number increases. The validation error decreases up to a certain point during training and then increases. This increment represents the point of model over fitting. Therefore, the optimal neuron number for gbellmf algorithm is three neurons, Figure 5. The optimal neural network structure for NF-GVEIN methodology is given on Figure 3.

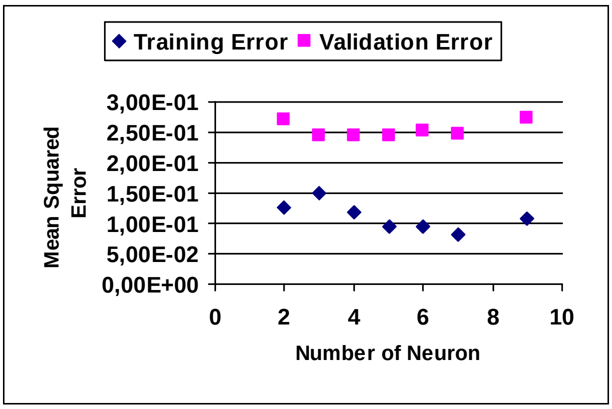

Figure 5. Dependence between mean square error and neuron numbers

3.4. Design of graft by determining optimal Arteriovenous Graft-To-Vein Angle

The flow field data taken from the experimental analysis were used as input data. The AV graft to vein angle was changed from five degrees to thirty degrees respectively. The mean squared error (MSE) was found the least when the AV graft angle was nine degree. The value 0.23 of MSE is shown in Figure 6. The velocity data inside AV graft to vein anastomosis were determined at graft angles of five, nine, fifteen, and thirty degrees, Figures (7, 8). The velocity values were compared with the experimental measurement data taken at graft angle of five, Figure 4. The velocity values found at nine degrees angle are in similar structure with the original experimental data measured at five degree. However the magnitude of the velocities of experimental results is higher near the vein wall than the model. This shows the more fluctuated structure near the wall. This highly fluctuated structure can cause the wall vibration which can lead to the formation of the intimal hyperplasia inside the wall. The magnitude of the velocity at the measurement point of 0.4 near the vein wall was approximately 2.8 m/s at graft angle of five whereas the same value was 2.3 m/s at angle of nine degrees, 2.5 m/s at angle of fifteen degrees and 2.3 m/s at angle of thirty degrees. The velocity values at nine degree angle are lower and smoother than the original velocity values. The velocity profile is getting blunter due to the structure of the flow inside the AV graft to vein anastomoses at nine degree graft angle. Therefore NF-GVEIN determines the optimal angle as nine degrees for this in vitro model and thus supports the design of the AV graft.

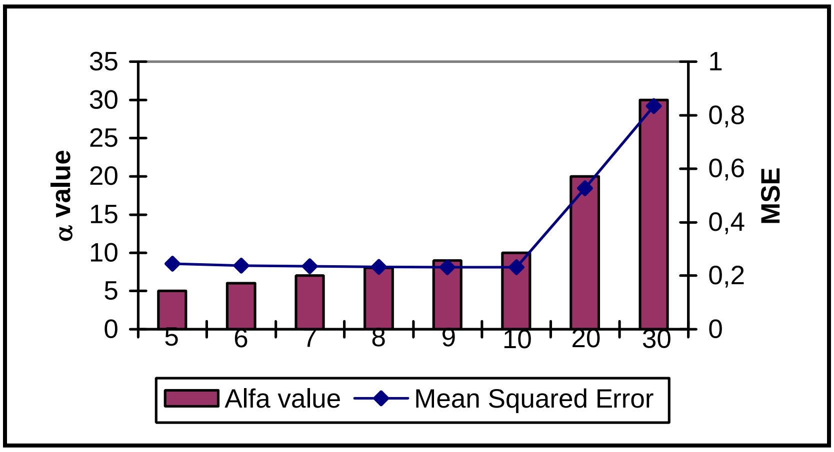

Figure 6. NF-GVEIN model mean squared error (MSE) results

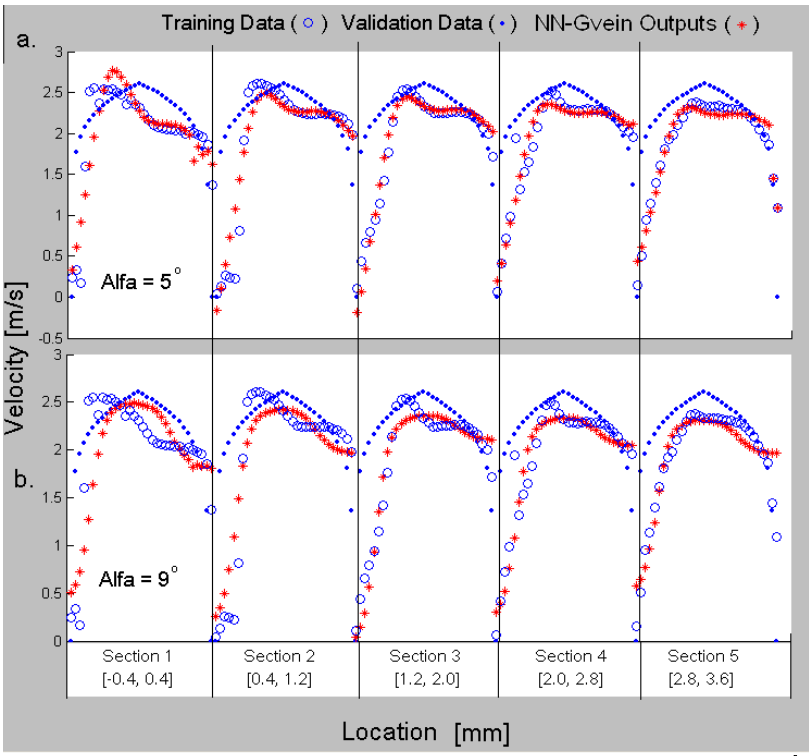

Figure 7. Velocity profiles in the AV graft-to-vein connection for $\alpha = 5^0$ and $\alpha = 9^0$

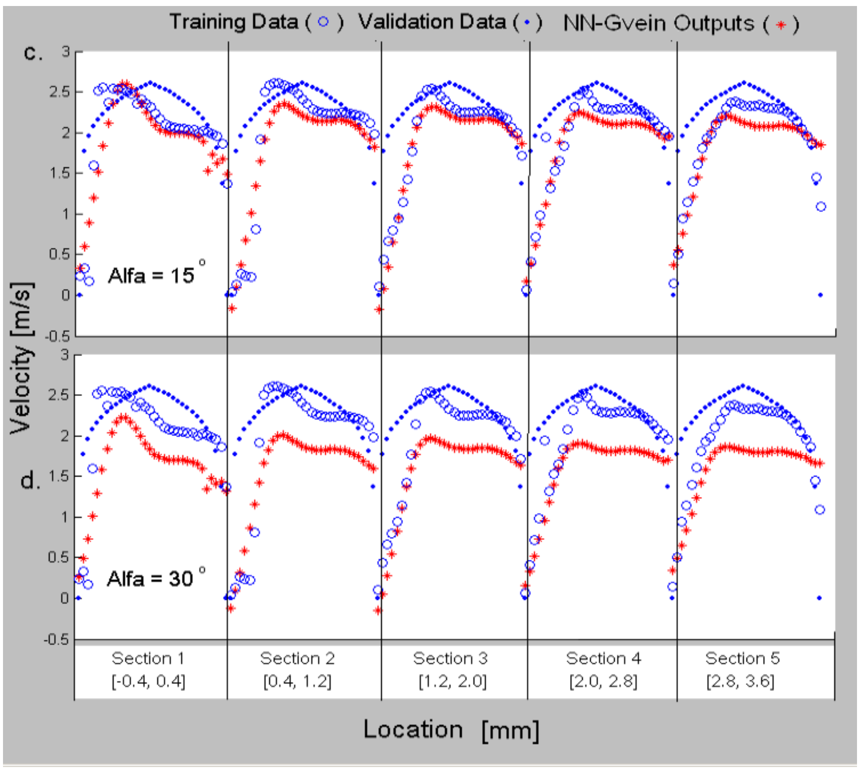

Figure 8. Velocity profiles in the AV graft-to-vein connection for $\alpha = 15^0$ and $\alpha = 30^0$

4. CONCLUSION

A novel methodology NF-GVEIN for AV graft design by turbulent field modeling is presented. It is based on LDA measurements and a hybrid neuro-fuzzy model ANFIS. The performance of the modeling was evaluated by comparison of the measured and the modeled flow velocity values. NF-GVEIN can be applied to various problems in cardiovascular area such as the connections with bypass grafts or AV grafts and the results can be compared to the ones performed by experimental methods. Since the experimental studies are very expensive to set up and requires complex equipment and experts this method will be very helpful in this area to characterize the flow field inside the cardiovascular system. NF-GVEIN could be further developed for determining the intermediate velocities between any two measurement lines along the bifurcation plane.

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