NF-GVEIN: ADAPTIVE NEURO-FUZZY BASED MODELLING OF FLOW FIELD INSIDE GRAFT-TO-VEIN CONNECTION UNDER STEADY FLOW CONDITIONS

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ABSTRACT

This paper presents the application of the adaptive neuro fuzzy inference system (ANFIS) to a model of the flow field inside an in vitro arteriovenous (AV) graft-to-vein connection implanted to the kidney patients. A model based on ANFIS is proposed. Its relevant steps oriented to find the optimal AV graft angle are given. The advantage of this neuro-fuzzy hybrid approach 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. The model parameters and the fully developed turbulent velocity profile are defined. The model 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 closest to the fully developed turbulent flow was obtained. The simulation results showed that this model is feasible for forecasting of the optimal AV graft angle of the flow field series inside AV graft-to-vein connection. The results are highly promising, and a comparative analysis suggests that the proposed modeling approach outperforms artificial neural networks and other traditional time series models.

Key Words: Neural networks; fuzzy logic; fuzzy inference system; time series modeling; arteriovenous; stenosis; hemodynamics

Submission Area: Automation, computational intelligence, systems modeling & simulation
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1. Introduction
Extensive numerical [4], [8] and experimental [6], [11] 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 intimal hyperplasia and other forms of arterial disease. A further motivation is that the 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 dynamic details for arteries in general. Somewhat similar geometry occurs at the downstream end of an AV anastomosis created by incorporation of a loop of graft material 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 geometries when forming the end-to-side anastomosis between the graft and the vein. Kanterman et al. have shown that hyperplastic stenoses occur predominantly in the proximal venous segment (PVS), downstream of the graft-to-vein junction, as shown in Figure 1. This suggests the possible involvement of disturbances to flow created in the graft-to-vein junction and advected downstream. To date there has been only one detailed set of investigations [14] of the fluid dynamics of the graft-to-vein anastomosis. Shu et al. obtained the mean velocity profiles and wall shear stress (WSS) inside realistic AV graft models. They implicate 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 [1]. They tried to understand the location of the wall shear stresses and turbulence regions inside an AV graft model under steady and pulsatile flow conditions. The above mentioned modeling techniques [4], [6], [8], [11] did not use neural networks and fuzzy logic. We assume that the application of neuro-fuzzy models like [7], [8], [13] will help to create better model of the flow field inside the graft to vein connection and determine the optimal graft to vein angle.

In this paper, by using the neuro-adaptive learning technique ANFIS, a model of the flow field inside graft-to-vein connection under steady flow conditions (NF-GVEIN) is described. It is applied for forecasting of the optimal AV graft angle of flow field.

2. Description of NF-GVEIN Model
The NF-GVEIN model was created to facilitate the defining best application conditions for the values of the AV graft angle \( \alpha \) in graft to vein connection. Figure 1 shows the steps for determining the optimal \( \alpha \). 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, called adaptive neuro-fuzzy inference system (ANFIS) [3] is employed. Neuro-fuzzy modeling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modeling or to a fuzzy inference system. 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, etc. 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 model is the optimization of the model regarding \( \alpha \) value.
Figure 1. NF-GVEIN model sequence of steps
2.1. ANFIS architecture

The basic structure of the fuzzy inference system that 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 6. 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 [7], [12]. 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.

2.2. Defuzzification

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 [3]. It amalgamates two procedures, the logic decision and defuzzification procedures into one composite procedure.

3. Case Study

For illustrating the NF-GVEIN model a case study with experimental data shown in Figure 3 was carried out.

3.1. NF-GVEIN Model Parameter Definition

Four input parameters and one output parameter were defined (cf. Table 1). They are essential for accurate modeling of the flow field inside an AV graft-to-vein connection data. Two dimensional space (2D) was considered, X and Y were the measurements locations in the bifurcation plane of the in vitro mode (cf. Figure 2). The arteriovenous graft angle was specified as $\alpha$ 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 (cf. Table 1). By DVS is denoted the distal vein segment and by $x/D$ the non-dimensional coordinate system.

![Figure 2. Geometry and nomenclature of the venous anastomosis of AV graft model](image-url)
Table 1. Parameters of NF-GVEIN Model

<table>
<thead>
<tr>
<th>PARAMETERS</th>
<th>DIMENSIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>1. Measurement location X</td>
<td>mm</td>
</tr>
<tr>
<td>2. Measurement location Y</td>
<td>mm</td>
</tr>
<tr>
<td>3. Graft angle $\alpha$</td>
<td>degrees</td>
</tr>
<tr>
<td>4. Flow rate</td>
<td>mm$^3$/s</td>
</tr>
<tr>
<td><strong>Output Parameters</strong></td>
<td></td>
</tr>
<tr>
<td>1. Velocity $U_i = \sqrt{u_x^2 + u_y^2}$</td>
<td>cm/s</td>
</tr>
</tbody>
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3.2. Data Collection

Velocity profiles were measured as millimeter-spaced points along the bifurcation plane. 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 ($x = -6.8D$). On this basis, detailed measurements for the higher Reynolds numbers Re were confined to the graft inlet, the furthest proximal axial location within the anastomosis, and the PVS.

![Figure 3 Velocity profile of blood stream flow in graft-to-vein connection](image)

3.3. Definition of Fully Developed Turbulent Velocity Profile

For fully developed turbulent flows, the velocity profile [2] may be expressed as $V_{turb} = V_{max} \left(1 - r / r_{tube}\right)^{(1/m)}$ away from the laminar sublayer near the wall, where $m \sim 7$ for a wide range of Reynolds numbers. The fully developed turbulent flow velocity profile for our case study was calculated and illustrated in Figure 4.
3.4. Optimization of NF-GVEIN Model

For optimization of NF-GVEIN model the ANFIS algorithm with the lowest training error were selected, the optimal neural network structure was constructed and the optimal arteriovenous graft angle was determined.

3.4.1. Selection of the Algorithm

The performances of several ANFIS algorithms were determined with input MFs 3 3 3 3 neurons (cf. Figure 6). According to their training error the best algorithm for the modeling of the flow field inside graft to vein connection is gbellmf algorithm which has linear MFs with hybrid optimization method.

3.4.2. Construction of Optimal Neural Network Structure

As validation data set, the same input values of training data set was used. The output value of the validation data set was obtained from the fully developed turbulent velocity profile for each measurement line (cf. Section 3.3). 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 (cf. Figure 5). Therefore, the optimal neuron number for gbellmf algorithm is three neurons (cf. Figure 5). The optimal neural network structure for NF-GVEIN model is given on Figure 6.
3.5. Forecasting of Arteriovenous Graft-To-Vein Angle by NF-GVEIN

The flow field data taken from the experimental analysis were used as input data. The AV graft to vein angle was changed from nine degrees to thirty degrees respectively. The mean squared error (MSE) was found the least when the AV graft angle was nine degree. The magnitude of MSE is 0.23 shown in Figure 7. The velocity values were compared with the experimental measurement data taken at graft angle of five (cf. Figure 8). The values found at nine degrees angle are close to the original experimental data. For example the magnitude of the velocity in the middle of measurement point 0.4 was approximately 2 m/s at graft angle of five whereas the same value was 1.7 m/s at angle of 30 and 2.1 at angle of nine degrees. The velocity values at thirty degree angle are lower 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. NF-GVEIN finds the optimal angle as nine degrees for this in vitro model.

![Figure 8. Simulation of the NF-GVEIN model results: velocity profile in graft-to-vein connection for $\alpha = 30$, fully developed turbulent flow and $\alpha = 9$](image)

4. Conclusions

A novel approach for turbulent field modeling is presented. It is based on laser Doppler anemometer (LDA) measurements and hybrid neuro-fuzzy model ANFIS. In the experiment the flow inside the AV graft-to-vein connection was characterized using LDA. The performance of the modeling was evaluated by comparison of the measured and the modeled flow velocity values. This method 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 computational 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. Further development of NF-GVEIN could be for given flow in some region to forecast the flow in the surrounding region.

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