Neural network pattern recognition analysis of graft flow characteristics improves intra-operative anastomotic error detection in minimally invasive CABG

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Abstract

Objective: The intra-operative assessment of the quality of anastomosis in minimally invasive coronary artery bypass surgery (CABG) is critical. Recent investigations demonstrated that flow probes used intra-operatively to assess anastomotic errors may give the surgeon a false sense of confidence as only severely stenotic anastomoses (>90%) could be reliably detected. We developed a neural network system using graft flow data and assessed its potential to improve anastomotic error detection.

Methods: Mammary to LAD grafts (n = 46) were constructed in mongrel dogs off-pump. Continuous beat-to-beat graft flow was recorded using transit-time flow probes. Various degrees of anastomotic stenoses (0–100%) were created by an additional suture. The degree of anastomotic stenosis was confirmed by postoperative angiography. A learning vector quantization neural network was created using heart rate, mean aortic pressure, mean systolic, maximum systolic, minimum systolic, mean diastolic, maximum diastolic, minimum diastolic, and mean graft flows. In addition, a spectral analysis of the flow waveforms was performed and the magnitude and phase of the first five harmonics were used to further develop the neural network.

Results: The neural network pattern recognition system was 94% accurate in detecting any stenosis <50%. To validate the model, a testing set was used with 20% of the data values, and the accuracy remained at 100% above chance alone.

Conclusion: Pattern recognition of transit-time flow probe tracings using neural network systems can detect anastomotic errors significantly better than the surgeon’s visual assessment, thereby improving the clinical outcome of minimally invasive CABG. © 1999 Elsevier Science B.V. All rights reserved.

Keywords: Anastomotic Quality; Off-pump; Coronary artery bypass surgery

1. Introduction

Coronary artery disease is the major cause of death in the US and worldwide [1]. Coronary artery bypass surgery (CABG) and interventional cardiology procedures in the form of balloon angioplasty (PTCA) with or without stenting, are the best therapeutic modalities to treat this condition. In the last decade, there has been a change in the characteristics of patients presenting for CABG. Most patients now are elderly with severe co-morbid illnesses. It is no wonder that there has been an increase in mortality in the recent years despite the vast progress in supporting technology.

Over the past several years, there has been a growing trend toward performing CABG surgery off-pump [2]. It is believed that during conventional CABG using CPB, the blood component recognizes the machine as a foreign body, and elicits a vast inflammatory reaction, which may cause lung, kidney, and/or other organ damage. Further, we have shown that a large number of micro-emboli may be released in the systemic circulation as a result of using CPB, which may lead to neurological impairment [6]. These potentially adverse effects of CPB have prompted greater interest in performing CABG procedures without the use of the CPB machine. The off-pump procedure is technically more demanding, and has not been completely embraced.

The recent introduction of minimally invasive heart surgery through a small incision raised great enthusiasm among surgeons, cardiologists, and patients [3]. The combination of small wound, reduced cost, shorter hospital stay, and the avoidance of the CPB machine have helped this
procedure gain more interest [4]. Recent reports by our group and others have shown excellent results for this procedure comparable to those of conventional surgery [5,6]. However, this procedure is still being performed on the beating heart and the probability of a technical error is greater than the conventional CABG with the aid of the CPB machine and cardioplegic arrest.

Previously, we have shown that mean graft flow and graft-flow waveform morphology can be used to reliably detect nearly occluded and patent grafts, but cannot be used to distinguish other degrees of stenosis [7–10]. We conducted a survey of 20 cardiac surgeons to assess their ability to detect anastomotic errors by evaluating mean flow and flow waveform morphology [7]. They were able to clearly identify a highly stenotic graft (>90% stenosis), however, 24% would redo a fully patent anastomosis, 58% accepted an anastomosis with moderate stenosis, and 72% accepted anastomoses with severe stenosis. In this paper, the ability to detect anastomotic error using an improved analysis technique of graft flow is investigated.

The main objective of the study was to determine whether graft flow can reliably determine whether the anastomosis was ‘acceptable’ (more than 50% open) or ‘should be redone’ (less than 50% open). In this study, graft flow physiological parameters calculated on a beat-to-beat basis were used to build and test a neural network. A fast fourier transform (FFT) was applied to the graft flow data and the resulting spectral information (magnitude and phase) was also used to build and test the neural network.

2. Methods

The process of data mining encompasses the full range of data needs: sampling, exploring, modifying, modeling, and assessing (SEEMMA) [11]. All five steps of the data mining process were needed and used to examine the effectiveness of graft-flow measurements to predict graft quality outcomes.

2.1. Sampling

2.1.1. Surgical technique

Twenty-seven mongrel dogs (25–35 kg) were anesthetized with Nembutal (30 mg/kg) and maintained on 2% Isoflurane. Respiration was maintained with a volume control respirator on 100% oxygen. Continuous ECG was monitored throughout the procedure. Arterial blood gases were sampled every 30 min, and bicarbonate added as needed to maintain a physiologic pH between 7.35 and 7.45. Aortic blood pressure was monitored using a 5F-micromanometer-tipped catheter (Millar Instruments, Houston, TX) introduced through the femoral artery. Through the left fifth interspace anterolateral thoracotomy, the left and right mammary arteries were dissected from their origin to their bifurcation and wrapped with gauze soaked in papaverine solution (1 cc of papaverine diluted in 10 cc of normal saline).

The pericardium was opened and the margins sutured to the edges of the wound. The LAD distal to the first diagonal was selected for grafting the left mammary artery followed by grafting the right mammary to the proximal LAD. The anastomotic region was controlled proximally and distally with 3.0 prolene snare. Heparin (1 mg/kg) was given intravenously followed by two periods of ischemic preconditioning (3 min each) before opening the selected site of the LAD. A cardiac stabilizer (Origin, Menlo Park, CA) was used to mechanically stabilize the grafting site. The mammary to LAD anastomosis was then constructed ‘off-pump’ using 7.0 continuous prolene suture technique. The proximal LAD was snared and completely occluded during all experimental conditions. Stenosis was created by passing a suture (8.0 prolene) across the internal thoracic artery at the anastomosis with the left anterior descending coronary artery. After multiple preliminary experiments, the depth of the suture was varied to produce mild (<25%), moderate (<50%), moderately severe (<75%), or severe (>75%) stenosis. The degree of obstruction was confirmed and graded by random angiography.

All animals received humane care in compliance with the ‘Guide for the Care and Use of Laboratory Animals’ published by the National Institutes of Health (NIH publication 85–23, revised 1985) and with approval by the University of Louisville Institutional Animal Care and Use Committee.

2.2. Exploring

2.2.1. Experimental design

Forty-six patents (<15% stenosis) left and/or right IMA grafts to LAD were constructed. Transit-time flow probes (Model 3SB, Transonic Systems Inc., Ithaca, NY) placed on the graft(s) were used to measure graft flow. Continuous beat-to-beat graft flow was recorded with the LAD occluded and the graft to LAD anastomosis under patent (<15%), mild (<25%), moderate (<50%), moderately severe (<75%), and severe (>75%) stenosis conditions. One-minute data sets containing graft flow (Q), arterial pressure (AoP), and ECG were analog-to-digital (A/D) converted, sampled at 100 Hz, and recorded using a MacLAB data acquisition system (MacLAB, Milford, MA) during each experimental condition. The degree of anastomotic stenosis was determined by random postoperative angiography.

2.3. Modifying

2.3.1. Data reduction

Beat-to-beat analysis of Q, AoP, and ECG for each 1 min data set (approximately 60 beats) were calculated using custom data reduction software developed in Matlab (MathWorks, Cambridge, MA). Mean arterial pressure (AoP_{mean}), heart rate (HR), mean (Q_{mean}), mean systolic (Q_{smean}), mean diastolic (Q_{dmean}), maximum systolic (Q_{smax}), maximum
There are two phases in neural computing: learning and recall. The learning phase (computed on a training set) is the phase during which the weights of the network are adjusted to yield the desired output. The weights are repeatedly adjusted until the prediction error is at a minimum or until it is determined that the network has adequately modeled the data in the decision space. The weights are then fixed and the recall phase begins. During the recall phase, the network produces the final output.

The values $X_0, X_1, X_2, \ldots, X_n$ represent the input vectors. These are the variables which are defined as either categorical or continuous and are used to predict the final outcome. The value $Y_j$ represents the final outcome for the $j$th observation. Known values of $Y_j$ are used to define the neural network, and to determine the effectiveness of the model.

The weights $W_{0j}, W_{1j}, W_{2j}, \ldots, W_{nj}$ are values assigned to the vectors $X_0, X_1, X_2, \ldots, X_n$ to determine in an adaptive manner just which of the elements of the vector $X_j$ should be more heavily emphasized than others in predicting the outcome $Y_j$. There are two phases in neural computing: learning and recall. The learning phase (computed on a training set) is the phase during which the weights of the network are adjusted to yield the desired output. The weights are repeatedly adjusted until the prediction error is at a minimum or until it is determined that the network has adequately modeled the data in the decision space. The weights are then fixed and the recall phase begins. During the recall phase, the network produces the final output.
is tested for its ability to generalize to the prediction problem on data not seen previously. Prediction error can then be calculated to determine the ability of the network to generalize to new data. Neural networks depend very heavily on the ‘gold standard’ of a validation set. This is the one difficulty in preventing general acceptance of neural networks. The rules are contained in a ‘black box’ so that no one equation emerges defining the weights. Additional data must be input into the neural network process to determine the accuracy of prediction.

For this dataset, the learning vector quantization (LVQ) was the optimal choice of neural network. It is particularly useful when the categorization has a 20–80 split in the data. This method assigns vectors of values to different classes. This assignment is made by examining the distance between the training vector and a processing element. The nearest processing element is the ‘winner’. If it is in the same class as the training vector, it is moved closer; otherwise, it is moved away. Thus, processing elements assigned to the same class are moved to the same region of the network. The winning processing element (the one nearest the training vector) is adjusted by the formula:

\[ w' = w + \alpha(x - w) \]

if the winning PE is in the correct class.

Since logistic regression is the more traditional method of analysis, the results of the neural network analysis were compared to those of logistic analysis. Specifically, measures of sensitivity, specificity, positive and negative predictive values and accuracy were compared using the entire data set and a 80–20 split (80% of the sampled data were used to develop a neural network and the remaining 20% were used to test it). The receiver operating curves for the logistic regression and neural network analysis were plotted and compared for ‘goodness of fit.’

3. Results

Sample graft flow tracings for varying degrees of stenosis are shown in Fig. 2. Magnitudes and phases from spectral analysis (FFT) for ‘good’ and ‘bad’ anastomoses are illustrated in Fig. 3. The odds ratios and \( P \) values for all calculated variables using the logistic regression are listed in Table 1. The receiver operating curve for logistic regression and neural network analysis are shown in Figs. 4 and 5, respectively. The area under the logistic regression curve was 0.71, indicating a moderate prediction accuracy, compared to 0.94 for the neural network analysis curve, indicating excellent prediction accuracy. The neural network analysis performed better than the logistic regression at a cutpoint of 0.50 for all measurement criteria using the entire data set (Table 2), and using an 80–20 split (Table 2).

![Figure 3: Example of magnitude and phase information for first five harmonics from spectral analysis (fast fourier transform) of IMA graft flow waveforms for ‘good’ (<15% stenosis) and ‘bad’ (>75% stenosis) anastomoses with LAD occluded. LADc-IMAo, LAD closed and IMA patent; LADc-IMA > 75, LAD closed and IMA with greater than 75% stenosis.](image-url)
3) the results were far superior specificity and false negative rate yielding an overall superior accuracy.

4. Discussion

Neural networks have been defined in many ways. One good definition is that neural networks are massively parallel interconnected networks of simple elements and their hierarchical organizations, which are intended to interact with the objects of the real world in the same way as the biological nervous systems do. A neural network attempts to find a mathematical process which will provide the desired output given only the input variables. There are two primary reasons to use neural networks: computational power and ease of use [16]. Neural networks are very sophisticated modeling techniques, capable of modeling extremely complex functions. In particular, neural networks are nonlinear and can be used with dependent sets of data. Further, since neural networks learn by example, the user simply needs to gather representative data, and invoke training algorithms to automatically learn the structure of the data.

Off-pump minimally invasive surgery is still in its infancy. One of the main reasons that general application of off-pump surgery has been delayed is that there is a high probability of technical error. In addition, it is difficult to gage the degree of anastomosis through non-invasive techniques. There appears to be a growing number of physicians who use transit-time flow probes to measure graft flow for detecting anastomotic error. Our own clinical experience showed that intraoperative measurements of graft flow may be misleading [7]. Therefore, we set out to determine whether graft flow was a viable clinical tool for assessing anastomotic quality. Due to the logistics, time constraints and patient care, we found it more appropriate to conduct a study in an animal model first. Our preliminary findings confirmed our suspicions that graft flow can be misleading [8]. The objective of the research presented in this paper was to extrapolate additional information from graft-flow measurements (waveform characteristics and spectral content). These data were then used to train a neural network that could substantially increase the accuracy and reliability in classifying various degrees of stenosis, thereby improving the surgeon’s ability to detect anastomotic errors.

Graft flow measurements can be used to estimate the anastomosis effectively using time-based physiological parameters in combination with frequency-based information from spectral analysis. A ‘cutpoint’ for ‘accepting’ an anastomosis was defined as 50% patency. A neural network was trained to estimate high or low patency at the cutpoint value. It was clearly demonstrated that the neural network was effective in the estimation of anastomotic quality (Tables 2 and 3). It was further demonstrated that the neural network was a far better estimator than traditional logistic regression (Tables 2 and 3; Figs. 4 and 5).

Table 2
Comparison of outcome measures for neural network analysis versus logistic regression when using the entire sampled dataset: these outcomes act to classify using a cutpoint of 50% stenosis.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Neural network analysis (%)</th>
<th>Logistic regression (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>98.6%</td>
<td>86%</td>
</tr>
<tr>
<td>Specificity</td>
<td>82.1%</td>
<td>35%</td>
</tr>
<tr>
<td>Positive predictive value</td>
<td>93.5%</td>
<td>80%</td>
</tr>
<tr>
<td>Negative predictive value</td>
<td>95.8%</td>
<td>45%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>94.1%</td>
<td>73%</td>
</tr>
</tbody>
</table>

Table 3
Comparison of outcome measures for neural network analysis versus logistic regression when using a 20% validation set. These outcomes are to classify using a cutpoint of 50% stenosis.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Neural network analysis (%)</th>
<th>Logistic regression (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>73%</td>
<td>88%</td>
</tr>
<tr>
<td>Specificity</td>
<td>84%</td>
<td>30%</td>
</tr>
<tr>
<td>Positive predictive value</td>
<td>73%</td>
<td>80%</td>
</tr>
<tr>
<td>Negative predictive value</td>
<td>84%</td>
<td>43%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>80%</td>
<td>76%</td>
</tr>
</tbody>
</table>

Fig. 4. Receiver operating curve for logistic regression analysis with sensitivity plotted versus 1-specificity of predicted outcomes.

Fig. 5. Receiver operating curve for neural network analysis with sensitivity plotted versus 1-specificity of predicted outcomes.
The results of this study in dogs are encouraging. However, it must be realized that there may be other important variables which are excluded in canine experiments such as initial coronary artery disease beyond the point of the anastomosis. We believe that this technique may be of value clinically. Our vision is to develop a clinical database of graft-flow measurements correlated to varying degrees of anastomotic stenosis, validated by a ‘gold standard’ (angiography). These data would then be used in the development of a ‘black box’ device that assesses a graft flow waveform in real-time and quickly provides feedback to the surgeon as to the classification of the degree of stenosis.

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References


Appendix A. Conference discussion

Professor T. Treasure (London, UK): The surgeon wishes to know how good the anastomosis is. Have you got any data validating the neural network against the angiographic outcome?

Dr Cerrito: The experiments were conducted in animals allowing more flexibility in measurement. The level of stenosis was randomly verified via angiography to compare the outcome of the neural network.

Professor Treasure: And your stitched stenosis is sort of comparable with what you would see in angiography subsequently?

Dr Cerrito: Yes.

Dr B. Walpoth (Bern, Switzerland): It is a nice model. However, in our hands spectral analysis was not very useful since we had problems interpreting our results. My main question is what is the weight of the absolute flow values in your model? For us as surgeons, a coronary graft flow around 50 ml/min is good and satisfying. Whereas, if we measure a flow below 10 ml/min, we are worried. In addition, of course, we analyze the flow pattern, as you suggested, which will help us (whether it is more systolic or more diastolic) make decisions.

Dr Cerrito: There is a lot of variability between different subjects and within subjects. The use of mean flow in measurements filters out much of this variability to the point where few subjects have flow patterns that are recognizable in terms of stenosis. Therefore, the harmonics from the spectral analysis are needed to analyze flow allowing for the possibility of variability. The neural network is a ‘black box’ which assigns multiple weights to the input variables, including the harmonics, to predict outcomes. The pattern recognition requires the use of all input variables; mean flow is not sufficient.

Dr A. Murday (London, UK): As I understand it, using neural networks, you could actually choose any degree of stenosis that you care to measure, so that in fact you could have a whole range. The question therefore arises, as to what degree of stenosis coronary surgeons should be prepared to accept.

Dr Cerrito: You are right. Given a large enough data sample, you can make multiple cut points. Because we only had 27 dogs and 46 grafts, we could only do one cut point. If we had, say, 200, 300 data points, we could make finer and finer cuts.

Dr Murday: So what stenosis should we be prepared to accept?

Dr Cerrito: That, I would say, is up to the surgeons.