The Performance of Neural Network in the Estimation of Cardiac Output Using Arterial Blood Pressure Waveforms

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Abstract

The ability of accurate measuring of cardiac output (CO) in clinical medicine is important as it is provided for improved diagnosis of abnormalities, and can be used to guide the appropriate management. Estimation of cardiac output from arterial blood pressure (ABP) waveforms has received considerable attention in recent years. So far, various estimation methods are used for the measurement of CO from ABP. However, these estimators have several limitations and sometimes don't have good performance. Neural network is usually useful for function approximation and it can improve the performance of estimators. In this study, we evaluate and compare the performance of 3 CO estimation methods with neural network on a large set of clinical data, using the simultaneously available Thermodilution CO (TCO) measurements as gold-standard. For estimation purposes, we applied two neural networks of Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF). Proposed scheme modifies the coefficients of estimators which have been applied to the previous CO estimation methods. The results, comparing with previous methods, show noticeable reduction in the mean absolute error between TCO and CO estimation. .

1. Introduction

Due to the rapid increase of the incidence of cardiovascular diseases, the requirement of detecting and monitoring the cardiovascular function is more diversified than ever. Hemodynamic parameters such as cardiac output, stroke volume, cardiac index, stroke index, total peripheral resistance and blood pressure have significant clinical meanings to describe human cardiovascular function [2]. Unfortunately, Current clinical methods for determining cardiac filling pressure and cardiac output require catheterization of the right heart and are therefore restricted to a small fraction of the patients, commonly a subset of those in intensive care unit, because this method is highly invasive. Even in those circumstances in which a pulmonary artery catheter is in place, measurements of left ventricular filling pressure and cardiac output are commonly performed intermittently, as they require the proper placement and inflation of the balloon-tipped catheter or the administration of cold saline into the pulmonary artery. Finally, the benefit of the pulmonary artery catheter has been called into question repeatedly, which might ultimately lead to a reduction in its use and consequently a reduction in the number of cardiac output measurements performed. There is evidently an essential need for automated (i.e. operator independent), continuous (rather than sporadic), and ideally non- to minimally invasive monitoring of absolute or even relative changes in cardiac filling pressure and cardiac output, especially when faced with an aging population [5]. The concept of using arterial pulse contour to infer cardiac output (CO) goes back to 1904[4]. The ABP waveform contains rich information about the cardiovascular system, such as heart rate, systolic, mean, and diastolic arterial pressures [1]. The accuracy of CO estimation from ABP has been well studied in the past. Three CO estimators studied in this study listed in the Table 1. All expressions given in the table 1 are proportional to CO. The proportionality constant encapsulates terms such as arterial compliance and peripheral resistance that are not obtainable from a given model [7]. Hence, they can't provide the good estimation. Neural network is usually advantageous for estimation and it can improve the performance of estimators. it modifies the coefficients of estimators. In this study, two neural networks were used to estimate cardiac output from arterial blood pressure and their performance was evaluated.

Table 1. Cardiac Output Estimators.

CO estimator	CO = k · below
Lilj	$Q = \dfrac{K}{P_s + P_d}.P_p.\text{f}$
Herd	$Q = (P_m - P_d) \cdot \text{f}$
Wesseling	$Q = K.(163 + \text{f} - 0.48.P_m).A_s.\text{f}$

2. Methods

2.1. Feature extraction

ABP data was taken from records in the Multi-Parameter Intelligent Patient Monitoring for Intensive Care (MIMIC) II database [8]. A 121-record subset was found which continuous ABP waveforms and simultaneous TCO measurements were available. ABP waveforms were sampled at 125 Hz with 8-bit quantization. TCO was available intermittently with a temporal resolution of 1 minute. A total of 27 records of ABP waveforms with 43 TCO measurements are used. The extracted blood pressure parameters included diastolic blood pressure (Pd), mean blood pressure (Pm), systolic blood pressure (Ps), pulse pressure (Pp = Ps − Pd) and pressure area during systole (As) [9],[7].The onset of each ABP pulse was detected using an implementation of Zong et al.'s wabp algorithm [1]. The SAI algorithm was evaluated on clinical ABP waveforms of 27 patients from MIMIC II and abnormal beats was removed using an implementation of James Xin Sun et al algorithm [6].

Extracted features in last section, like Systolic blood pressure, diastolic blood pressure and other features set in the input matrix to train the artificial neural networks. In this study, the two different architectures of ANN (MLP and RBF) were used for estimation of the cardiac output from ABP. To train the ANN, input vectors and target vectors randomly were divided into three sets as follows: 60% were used for training. 20% were used to validate the network generalization and to stop training before over fitting. The last 20% were used as a completely independent test for network generalization.

2.2. Pre processing

The performance of a MLP depends very much on its generalization capability, which in turn is dependent upon the data representation. One important characteristic of data representation is that is uncorrelated. In other words, a set of data presented to a MLP ought not to consist of correlated information. This is because correlated data reduce the distinctiveness of data representation and thus, introduce confusion to the MLP model during the learning process and hence, producing low generalization capability to resolve unseen data. This suggests a need for eliminating correlation in the sample data before they are being presented to the MLP. This can be achieved by applying the Principal Component Analysis (PCA) technique onto input data sets prior to the MLP training process as well as interpretation stage [3].

Before a set of data can be used for ANN training, they have to be pre-processed. The features were first normalized, so that they had zero mean and unity variance. We used the PCA to pre-process the training dataset, then for validation and testing the network with new inputs, we pre-processed them with the transformation matrix that was computed from the training set and applied it to a new set of inputs to the network already have been trained.

2.3. Neural network models (MLP, RBF)

For MLP training, we used a two-layer network, with tangent-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. Neurons number in hidden layers were selected from a series of trial runs of the networks having 1 neuron to 50 neurons in order to obtain the neuron number in the network with minimum error. Finally, we used 33-21 neurons in the hidden layers. The network has one output neuron because there is 1D target. We used the Levenberg-Marquardt algorithm for training. For RBF network, we first select a set of the spread parameter. In the analyses, network parameter of spread was set to 0.3.

For performance evaluation of the neural network in estimation of cardiac output, we considered two different models. In the first model, we used the features of any estimators as neural network's inputs. In the second model, we applied the combinations of features as neural network's inputs. After training, Mean Absolute Errors for both networks were evaluated and the results are shown in the tables 2, 3 and 4.

2.4. Post processing

For analysis of the network response, we putted the test data set through the network and performed a linear regression between the network outputs, after they have been mapped back to the original target range, and the corresponding targets. The results are shown in the Figures 1 and 2. The dashed line in each plot represents the perfect result (outputs= targets). The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. If R=1, this indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets.

3. Results

In this study, MAE for each of the two systems was calculated for the best performing training sets. In the first model, in analysis of the MLP network the Liljestrand method yielded the lowest error. The results show that, ANN can improve the performance of the CO estimation process rather than pervious. In the RBF model, the estimators are not well modelled and they have not good performance.

In the second model, in both of networks, the outputs seem to track the targets reasonably well, the R-values are almost 0.88 and the MAE is almost 0.55. Both networks have quite the same performance in the CO estimation, but totally the MLP network results are better. The minimum MAE in feature combination state reached to 0.54 L/min and the MRE for corresponding tests dataset reached to 9.82. These results are noticeably better than previous studies and noticeable results are achieved.

Table 2. MAE (L/min) Estimation with three different estimators.

CO estimator	MAE in MLP	MAE in RBF	Error in previous study
Lilj	0.85	1.2	0.92
Herd	0.94	1.5	1.24
Wesseling	0.99	1.1	1.10

Table 3. Result of R-value in estimators.

CO estimator	R-value with MLP	R-value with RBF
Lilj	0.85	1.2
Herd	0.94	1.5
Wesseling	0.99	1.1

Table 4. Estimation of the MAE (L/min) and MRE (L/min) with combination of estimator's features with RBF and MLP networks.

Combination of features	MAE	MRE	R-value
MLP	0.85	1.2	0.92
RBF	0.94	1.5	1.24

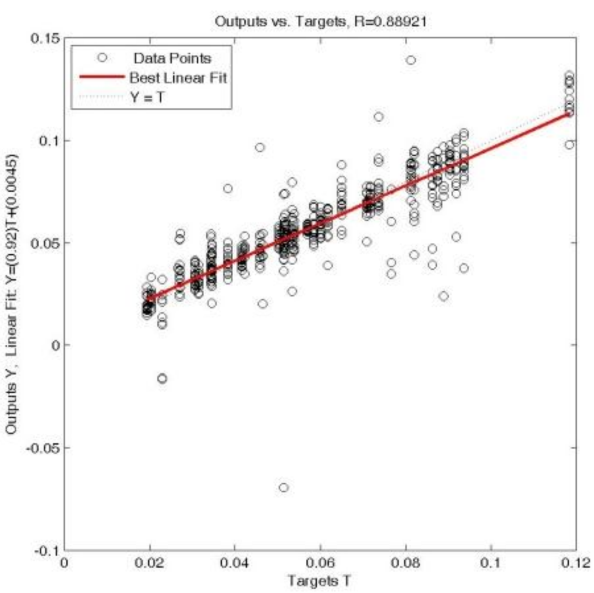

Figure 1. Result of regression for MLP in combination of features.

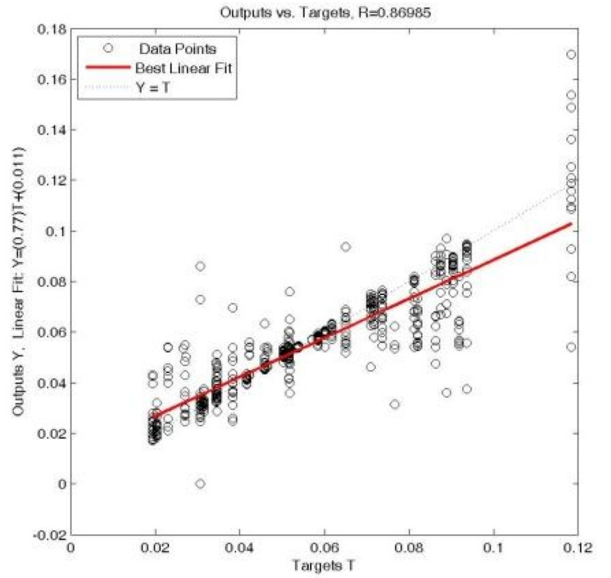

Figure 2. Result of regression for RBF in combination of features.

4. Discussion

This paper compared the performance of a multi-layer Perceptron network (MLPN) and a Radial Basis Function Network (RBFN) to estimate the cardiac output from Arterial Blood Pressure. However the comparison of the RBF and MLP network models indicates the good estimation capabilities of MLP model. Their accuracies are almost the same in second model. It was found that the time taken by RBF is less than that of MLP. limitation of the RBF model is that it is more sensitive to dimensionality and has greater difficulties if the number of units is large. Modification of the coefficients measures to account for these types of estimators will increase clinical utility of CO estimates from ABP.

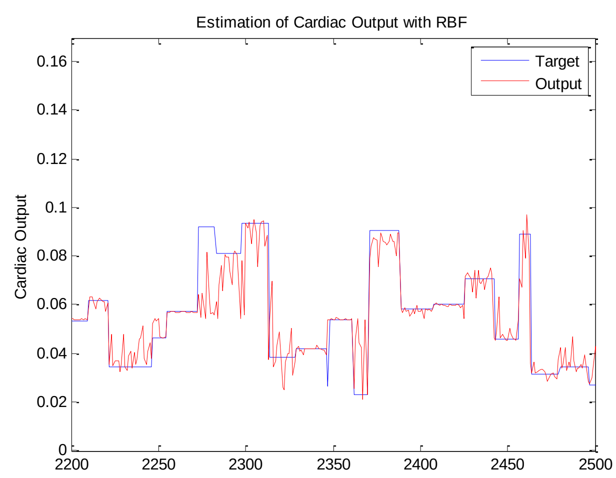

Figure 3. Result of the estimation of the CO with RBF in combination of the features in test dataset.

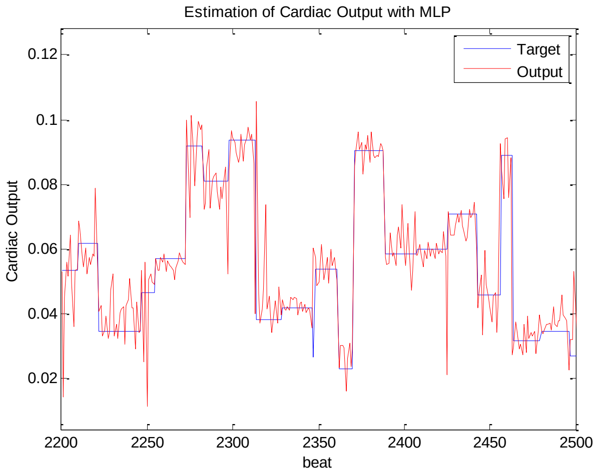

Figure 4. Result of the estimation of the CO with MLP in combination of features in test dataset.

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