Suction Detection in Left Ventricular Assist System: Data Fusion Approach

Seongjin Choi

Abstract: Data fusion approach is investigated to avoid suction in the left ventricular assist system (LVAS) using a nonpulsatile pump. LVAS requires careful control of pump speed to support the heart while preventing suction in the left ventricle and providing proper cardiac output at adequate perfusion pressure to the body. Since the implanted sensors are usually unreliable for long-term use, a sensorless approach is adopted to detect suction. The pump model is developed to provide the load coefficient as a necessary signal to the data fusion system without the implanted sensors. The load coefficient of the pump mimics the pulsatility property of the actual pump flow and provides more comparable information than the pump flow after suction occurs. Four signals are generated from the load coefficient as inputs to the data fusion system for suction detection and a neural fuzzy method is implemented to construct the data fusion system. The data fusion approach has a good ability to classify suction status and it can also be used to design a controller for LVAS.

Keywords: Data fusion system, left ventricular assist system, neural fuzzy system, suction detection, load coefficient.

1. INTRODUCTION

The left ventricular assist system (LVAS), where a blood pump is located between the left ventricle and the aorta, has been developed and is currently used as a bridge or a permanent treatment to patients whose hearts have functional problems. LVAS supports the heart to provide cardiac output at a pressure level appropriate to maintain adequate perfusion to the patient's body. LVAS using the nonpulsatile pump as an axial flow blood pump under investigation has advantages of small size, efficiency, and reliability over pulsatile pumps [1]. The nonpulsatile pumps require more careful pump speed control due to poor sensitivity to the ventricular preload and high sensitivity to the ventricular afterload. At high speeds, suction may occur at the inlet side of the pumps. Suction has a damaging effect on the myocardium, blood, and lungs and should be avoided. At low pump speeds, the pump does not provide proper cardiac output at adequate perfusion pressure and the pump speed must be increased to maximize pump flow without suction in the left ventricle. It is important to obtain necessary information such as pressures and flows of body to control the pump speed properly. Since the implanted sensors are unreliable for long-term use, sensorless approaches are investigated for suction detection in the left ventricle and pump speed control using available signals [2, 3].

Our goal is suction detection in the left ventricle from available signals of the pump speed console instead of invasive sensors measurements. A pump model is developed to provide the load coefficient of the pump. The load coefficient will be used as a signal to detect suction in the left ventricle without invasive sensors. In many patients, the natural heart still provides weak contractility during pump support, even though the amount of blood flow by the heart is insufficient to sustain the patient. This weak contractility contributes to the pulsatility of the hemodynamic signals as left ventricle pressure, pump flow, and aorta pressure with an implanted blood pump. The load coefficient of the blood pump presents the varying pulsatile load conditions to the pump and is also pulsatile.

While the load coefficient of the pump mimics the pulsatility property of the pump flow (only available with invasive sensors and unlikely available for long-term pump operation), it is difficult to use pulsatility information alone for suction detection. The reason is that pulsatility decreases before suction occurrence and increases after suction occurrence as the pump speed increases. As a result, a specific value of pulsatility can indicate both 'before suction' and 'after

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suction'. The mean value of the load coefficient is more distinct to indicate whether suction occurs and should be used to detect suction in cooperation with pulsatility information. These signal properties lead to the utilization of the data fusion system that combines available information (uncertain and incoherent information) and extracts necessary data for a particular purpose such as signal processing, image processing, and fault detection problems [4-6]. A recent data fusion approach to suction detection in LVAS can be found in [7], where the authors addressed the fact that the actual pump flow could be used to improve the performance of the data fusion system.

Inputs to the data fusion system are generally a combination of multiple sensor information. Since the only immediate information without invasive sensors is the fictitious load coefficient from the pump model, the data fusion system under consideration in this paper can be classified as a monosensor fusion system [8]. To provide more information to the data fusion system, several fictitious signals are generated from the load coefficient of the pump. These secondary signals are used as inputs to the data fusion system for the purpose of suction detection in the left ventricle. Candidate inputs to the data fusion system are pulsatility, change in pulsatility, mean value, and change in mean value of the load coefficient.

The data fusion system often uses fuzzy logic to deal with the problem of signal uncertainty thanks to an ability to handle uncertain signals [9,10]. The data fusion system employing fuzzy logic requires a careful choice of the membership function parameters because the membership function parameters are an important factor to performance of signal detection [11]. To avoid difficulty in choosing the parameters of the membership functions, a neural fuzzy technique is adopted to develop the data fusion system for suction detection. The parameters of the membership functions are trained to adjust the membership functions with a predefined training data [12]. Several types of inputs are investigated for the data fusion system and the results of suction detection are given and discussed.

Section 2 presents the pump model to provide the load coefficient. Also, the properties of the load coefficient and measured pump flow are examined. In Section 3, the data fusion system using the neural fuzzy method is constructed and the results of the data fusion system are presented. The conclusions are provided in Section 4.

2. SIGNAL EXTRACTION FROM PUMP MODEL

The nonpulsatile pump used in this paper is the Nimbus/UoP axial flow blood pump developed by Nimbus Inc. and the University of Pittsburgh. The model for this particular pump has been previously developed to estimate the pump flow and pressure difference across the pump and it uses current, pump speed, and pump flow as inputs to determine the parameters of the pump model by the least-squares method [13]. A similar approach has been adopted to develop another pump model. The pump model is given as follows:

$$J\frac{d\omega}{dt}=\frac{3}{2}K\ i-B\omega+L_{cof}\,\omega^3, \tag{1}$$

where ω is the pump speed [rad/sec], i is the motor current [A], J is an inertia coefficient of the rotor [$Kg{\cdot}m^2$], K is a torque constant [N·m/A], B is a coefficient of viscous friction [N·m·sec/rad], and L_{cof} is a load coefficient of the pump [$N{\cdot}m{\cdot}sec^3/rad^3$]. The model in (1) is a slight modification of the previously developed model in [13], which includes a product term of the flow and squared speed. The pump load model is similar to the model suggested by [14] and [15], where the load is modeled to be proportional to the squared speed. In this particular pump, the identification experiments show that the load model with cubic speed term is better than the load model with the squared speed term in terms of the least-squares method. The parameters of J, K, B, and L_{cof} of (1) are determined by the least-squares method. The off-line parameters of the pump model represent the average value of the parameters. With determined parameters J, K, and B, the load coefficient can be expressed as

$$L_{cof}(k)=\frac{1}{\omega(k)^3}\left(J\frac{\omega(k)-\omega(k-1)}{h}+B\omega(k)-\frac{3}{2}Ki(k)\right)$$

where h is a sampling time interval.

Animal experimental data has been used to compare the properties of the load coefficient to those of the pump flow. With pump implanted as LVAS in animal, the pump speed increased from minimum speed (837 rad/sec) to maximum speed (1570 rad/sec) for the first 140 sec and suction occurred around 80 sec. After 140 sec, the pump speed began to decrease to minimum speed. The change of pump speed provides changes in hemodynamic variables such as pump flow, left ventricle pressure, aorta pressure, and motor current to operate the pump.

The resulting pump flow and the load coefficient of the pump due to the change in pump speed are shown in Fig. 1(a) and Fig. 1(b). Both the pump flow and the load coefficient of the pump have pulsatility properties. To represent the amplitude of the pulsatility of the signal, the pulsatility index is introduced and extracted from the pulsatile signal using a simple extraction algorithm described in [3]. For example, the pulsatility index of the load coefficient L_{cof} can be obtained as

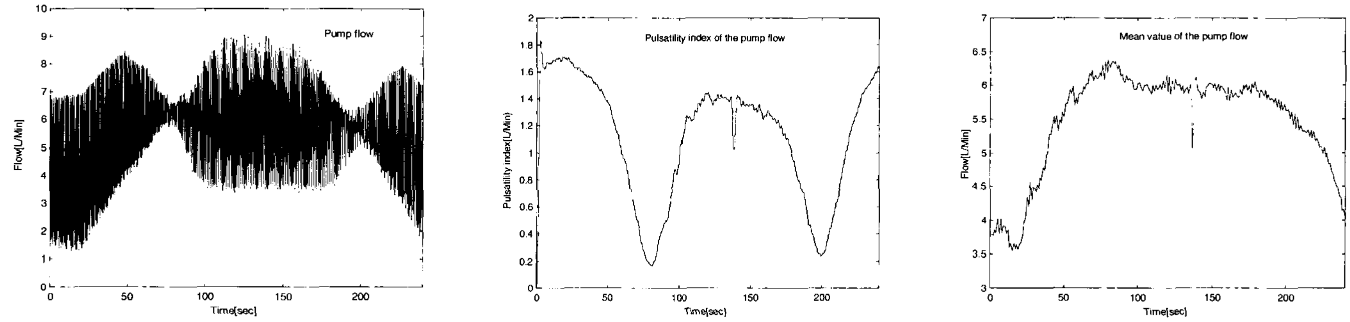
$$PL_{cof}(k) = G_l(abs(G_h(L_{cof}(k)))),$$

where G_l and G_h are low-pass and high-pass filters with cutoff frequencies of 0.25 Hz and 0.75 Hz, respectively, for extracting pulsatility of the load coefficient and PL_{cof} represents the pulsatility index of the load coefficient. Note that the pulsatility index of the signal has the same unit as the input signal and the unit of pulsatility index of the signal will not be explicitly indicated.

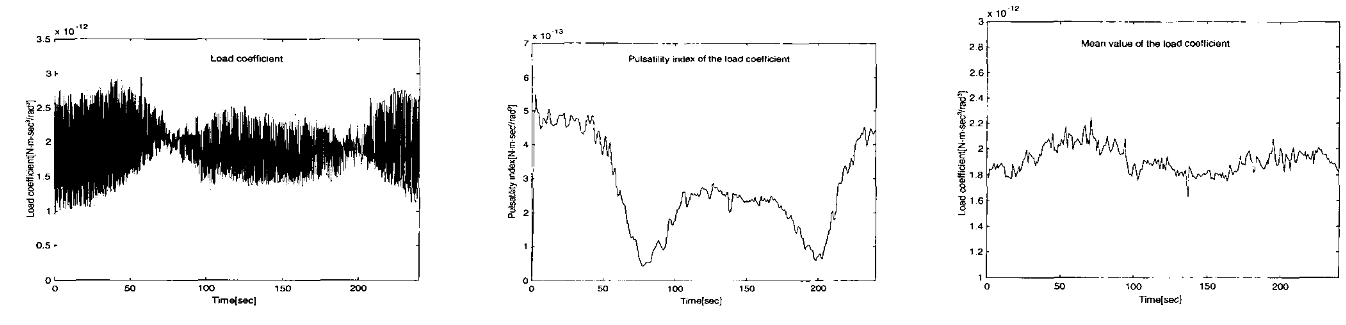
Fig. 1 also shows the tendency of the pump flow and the load coefficient to experience the occurrence of suction in the left ventricle. While suction occurs at 80 sec, the pump flow shows diminishing pulsatility before suction occurrence and increasing pulsatility after suction occurrence. The load coefficient also shows diminishing pulsatility before suction occurrence and increasing pulsatility after suction occurrence as the pump speed increases. The mean value of the pump flow decreases after suction occurrence (at 80 sec), maintains steady during complete suction period, but still decreases without recovering to normal values after the pump operating status returns to normal status (at 200 sec). Contrary to alternations of the mean value of the pump flow before and after suction occurrence, the mean value of the load coefficient continuously decreases after suction occurrence, maintains steady during complete suction period, and increases as expected with time delays after returning to normal pump operation status. That is, induction of suction in the left ventricle causes a drop in the mean value of the load coefficient. The change in mean value of the load coefficient can be used as an indication to suction detection. Signal property comparisons suggest that the load coefficient is a more desirable choice than the pump flow for suction detection due to the distinct change in mean value after suction occurrence.

3. DATA FUSION SYSTEM USING NEURAL FUZZY METHOD FOR SUCTION DETECTION

The data fusion system approach utilizes several signals as inputs to achieve the goal of system performance. The goal of the data fusion system under consideration is suction detection to avoid harmful effects to the patient with an implanted blood pump. The selected information as inputs to the data fusion system are mean pulsatility index, change in mean pulsatility index, mean value, and change in mean value of the load coefficient. Since the pulsatility of the load coefficient of the pump decreases to a minimum before suction occurrence and increases after suction occurrence with an increase in the pump speed, the pulsatility information is the most notable information for suction detection in the left ventricle. The mean value of the load coefficient is also significant information to indicate the suction occurrence as pointed out in Section 2. Signals such as changes in pulsatility and mean value of the load



(a)



(b)

Fig. 1. (a) Pump flow (left), pulsatility index of the pump flow (center), and mean value of the pump flow (right), (b) load coefficient (left), pulsatility index of the lod coefficient (center), and mean value of the load coefficient (right).

coefficient are also worthy to be investigated as inputs to the data fusion system.

The overall structure of the data fusion system for suction detection is given in Fig. 2(a). For the data fusion system employing the neural fuzzy method for suction detection, the input signals can be calculated from the following equations:

$$L_{cof}(k) = \frac{1}{\omega(k)^3}\left(J\frac{\omega(k)-\omega(k-1)}{h} + B\omega(k) - \frac{3}{2}Ki(k)\right),$$

$$PL_{cof}(k) = G_l(abs(G_h(L_{cof}(k)))),$$

$$MPL_{cof}(i) = \frac{1}{n}\sum_{k=1+(i-1)n}^{ni} PL_{cof}(k),$$

$$ML_{cof}(i) = \frac{1}{n}\sum_{k=1+(i-1)n}^{ni} L_{cof}(k),$$

$$CMPL_{cof}(i) = MPL_{cof}(i) - MPL_{cof}(i-1),$$

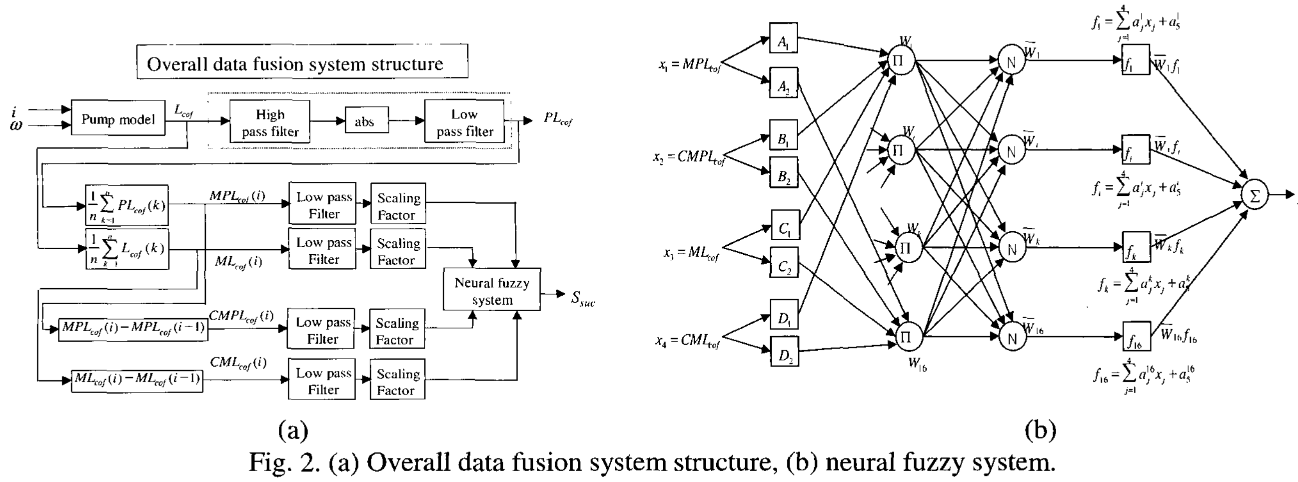
$$CML_{cof}(i) = ML_{cof}(i) - ML_{cof}(i-1),$$

where G_l and G_h are low-pass and high-pass filters with cutoff frequencies of 0.25 Hz and 0.75 Hz, respectively, for extraction of the pulsatility index of the load coefficient. While L_{cof} and PL_{cof} represent the instantaneous load coefficient and pulsatility index of load coefficient, ML_{cof}, MPL_{cof}, CML_{cof}, and $CMPL_{cof}$ represent the mean value of the load coefficient, mean pulsatility index of the load coefficient, change in mean value of the load coefficient, and change in mean pulsatility index of the load coefficient, respectively, over a specific period. Since the mean values of the signals are used as inputs to the data fusion system in Fig. 2, a time interval necessary to calculate the mean values of the signal is one of the important factors in evaluating the performance of the data fusion system.

Output of the data fusion system is suction status. While it is possible to use Boolean type classification, it is convenient to classify output as 'suction', 'imminent suction', and 'before suction'. The linguistic label can be related to a fuzzy logic scheme. Using fuzzy logic terminology, inputs can also be translated as 'low' and 'high'. The membership functions and rules for the data fusion system should be chosen to detect suction phenomenon. The design of membership functions for the fuzzy logic system requires a careful and tedious work to provide good performance. A neural fuzzy method, which can avoid difficulty in designing the membership functions, is introduced to construct the data fusion system [10]. The structure of the neural fuzzy system is shown in Fig. 2(b). The number of rules of the data fusion system is 16 and the total nodes of the data fusion system are 57 (8+16+16+16+1) for a four-input system.

The time interval for processing signals is selected so as to allow a reasonable detection time. A longer time interval can provide more distinguishable signal properties but it results in lengthy suction detection time and eventually harmful effect on the patient due to exposure to a long period of high pump speed. Also it reduces the number of the training data selected from the limited experimental data. Considering detection time and the number of the training data, 1 second is chosen as the time interval to calculate the mean values of the signals, which serve as inputs to the data fusion system for suction detection.

While inputs are calculated from the instantaneous load coefficient, output is determined by visual inspection of the experimental data correspondence to time sequence of the inputs. Each input signal can represent values of 'high' and 'low' in membership functions and output of the data fusion system is represented by values of 0, 0.5, and 1.0 corresponding



(a) (b)

Fig. 2. (a) Overall data fusion system structure, (b) neural fuzzy system.

to 'before suction', 'imminent suction', and 'suction', respectively. Fig. 3 shows the profiles of signals used for the data fusion system. Low pass filters are used to smooth the signal for inputs to the data fusion system.

The membership functions for each input signal are initially given and the membership functions are trained to fit into a given training data [10]. The training data consists of the inputs-output pairs from the animal experimental data. The training data is selected to have a 50% portion of the total available data. The rest of the data is used for the purpose of evaluation. The total available data is evenly divided into the training data and the test data. While the training data consists of inputs-output pairs at time step k, the test data consists of the inputs-output pairs at time step k+1.

To investigate the effect of the number and types of inputs to the data fusion system, several combinations of inputs have been used. First, mean pulsatility index and change in mean pulsatility index of the load coefficient were selected as inputs to the data fusion system. The data fusion system employing the neural fuzzy system has been trained and evaluated. The results are shown in Fig. 4(a). Secondly, the data fusion system, which used mean value and change in mean value of the load coefficient as inputs, has also been trained and evaluated. The suction detection results of the data fusion system with these inputs are shown in Fig. 4(b). Thirdly, mean pulsatility index and mean value of the load coefficients have been used as inputs to the data fusion system. The neural fuzzy system has been trained to construct the data fusion system. The results are shown in Fig. 4(c). Suction detection performances in Figs. 4(a) – 4(c) are not good enough to classify suction status in the left ventricle. Finally, mean pulsatility index, change in mean pulsatility index, mean value, and change in mean value of the load coefficient have been used as inputs to the data fusion system. Fig. 4(d) shows the evaluation results of the data fusion system with four inputs. It does apparently improve performance compared to the results in Figs. 4(a) – 4(c) and it demonstrates good performance of classifying suction status during the transient period from 'before suction' and 'suction' due to input signals such as $CMPL_{cof}$ and CML_{cof}.

Another factor considered in the data fusion system is output values of the inputs-output pairs necessary for training the data fusion system. Previously, outputs of the training data were classified

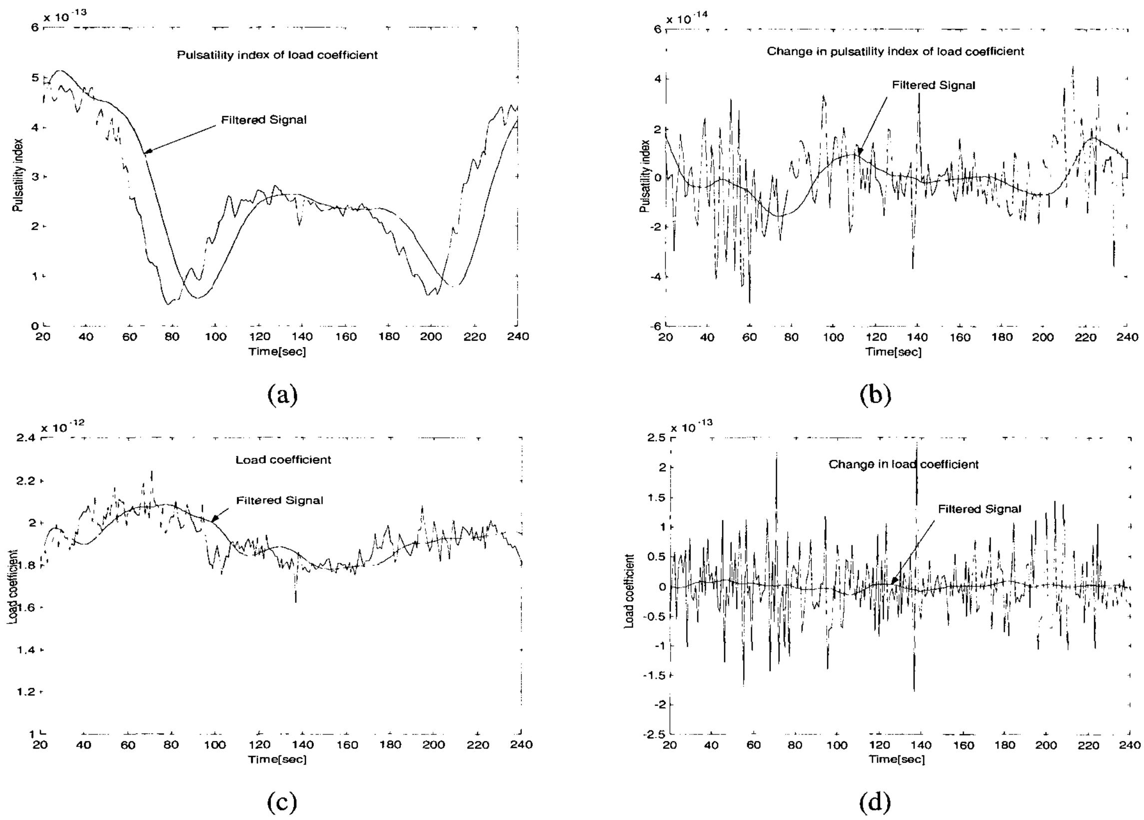


Fig. 3. Signals used for data fusion system. All signals are expressed as a unit of the load coefficient. (a) Pulsatility index of the load coefficient and filtered pulsatility index of the load coefficient, (b) change in pulsatility index of the load coefficient and filtered change in pulsatility index of the load coefficient, (c) load coefficient signal and filtered load coefficient signal, (d) change in the load coefficient and filtered change in the load coefficient.

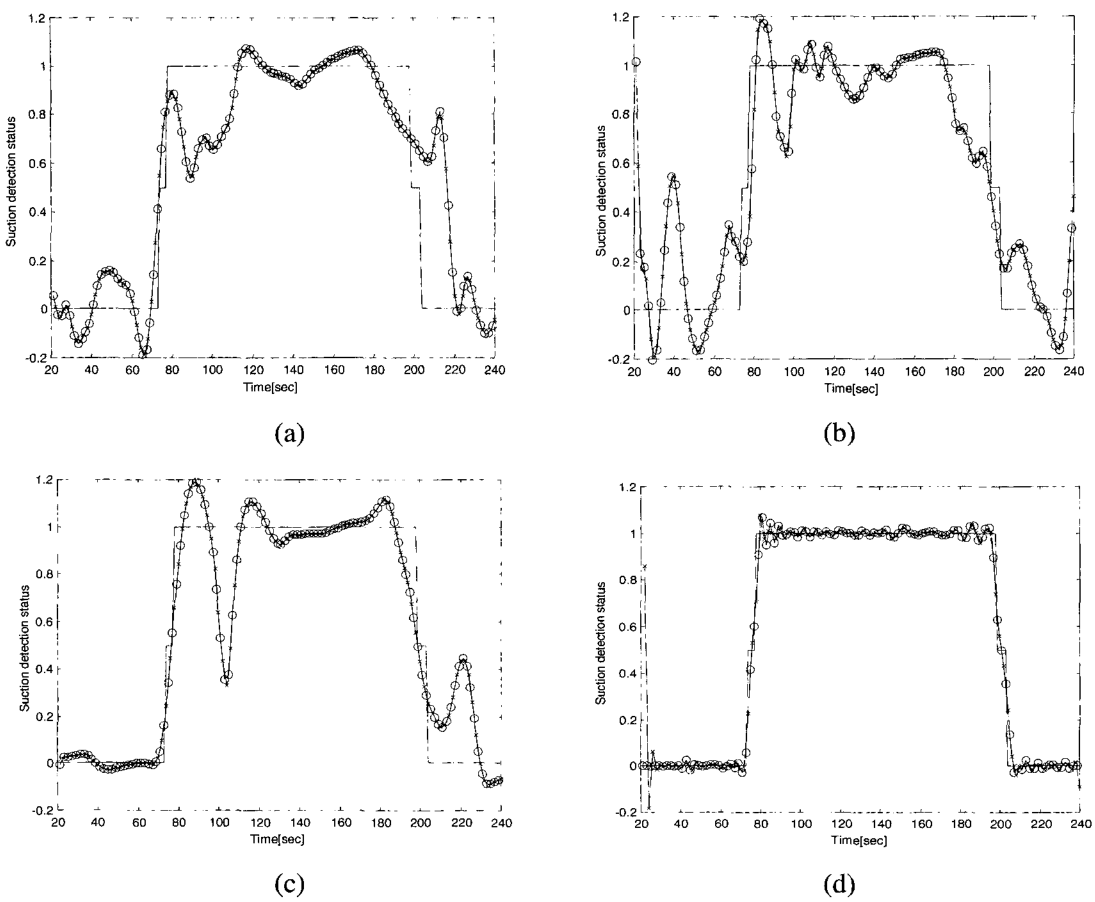


Fig. 4. Suction detection results. 'x' indicates the predicted suction status with evaluation data while 'o' indicates the expected suction status with training data. (a) Inputs: mean pulsatility index and change in mean pulsatility index of the load coefficient, (b) inputs: mean value and change in mean value of the load coefficient, (c) inputs: mean pulsatility index and mean value of the load coefficient, (d) inputs: mean pulsatility index, change in mean pulsatility index, mean value, and change in mean value of the load coefficient.

into three categories, 'before suction', 'imminent suction', and 'suction', represented by 0, 0.5, and 1.0, respectively. It may be helpful to describe 'imminent suction' more precisely to represent the intensity of imminent suction with values from 0 to 1. Identical procedures have been repeated to obtain inputs-output pairs of the training data and to train the data fusion system. The evaluation results are shown in Fig. 5. The four-input data fusion system can predict the transient suction status more precisely. It can be explained that changes in mean pulsatility and mean value of the load coefficient effectively capture the intensity of the imminent suction in the transient situation from 'before suction' to 'suction'. A simple modification of outputs of the training data can improve performance of the data fusion system. Overall, the data fusion system with four inputs shows good performance for suction detection and can be used to classify signals for this particular suction detection problem.

4. CONCLUSION

A data fusion system for suction detection has been developed without invasive sensors. The load coefficient is extracted from the pump model as an indicative signal to suction detection. Mean pulsatility index, change in mean pulsatility index, mean value, and change in mean value of the load coefficient have been chosen as inputs to the data fusion system. The data fusion system employing the neural fuzzy method has been trained with the inputs-output pairs from a portion of the animal experimental data. The trained data fusion system can predict suction status well and it can classify 'imminent suction' at several levels. The evaluation results are encouraging and the data fusion system can be incorporated with a controller for LVAS. Since the results depend on the limited number of the training data, an increase of the number of the training data can provide more diverse and realistic situations to the data fusion system and improve the performance of the data fusion system for suction detection in the left ventricle.

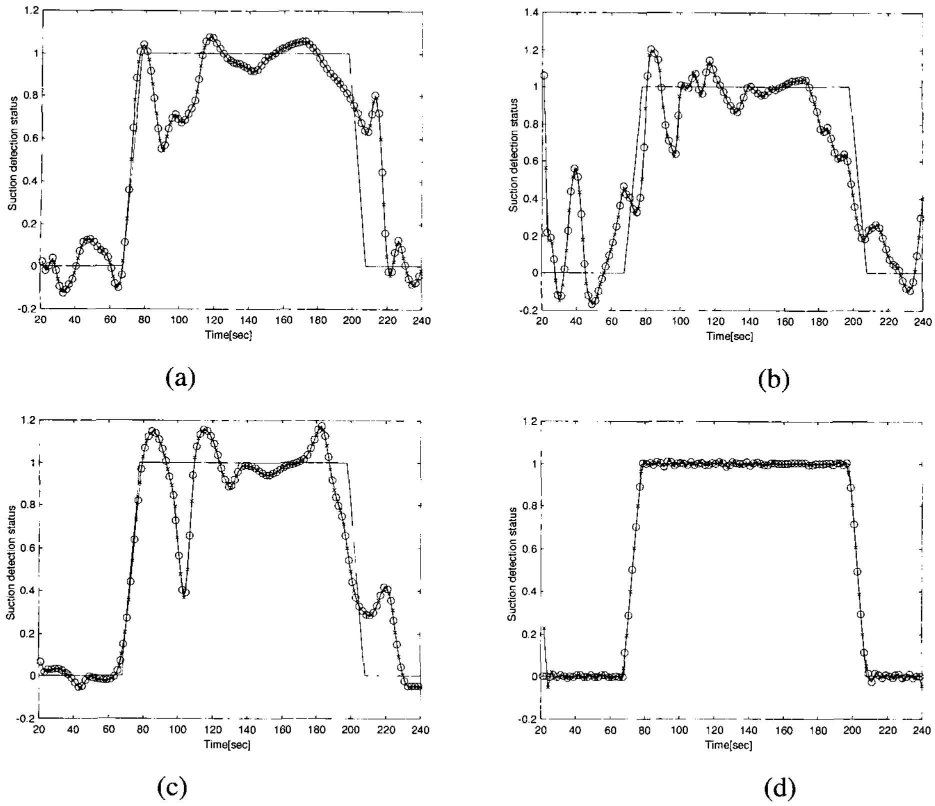


Fig. 5. Suction detection results. 'x' indicates the predicted suction status with evaluation data while 'o' indicates the expected suction status with training data. (a) Inputs: mean pulsatility index and change in mean pulsatility index of the load coefficient, (b) inputs: mean value and change in mean value of the load coefficient, (c) inputs: mean pulsatility index and mean value of the load coefficient, (d) inputs: mean pulsatility index, change in mean pulsatility index, mean value, and change in mean value of the load coefficient.

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