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A discriminant-analysis-based suction detection system for rotary blood pumps

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***Abstract*— A new suction detection system for rotary blood pumps used in Left Ventricular Assist Devices is presented. The system can correctly classify pump flow patterns, based on a discriminant analysis (DA) model that combines several indices derived from the pump flow signal to make a decision about the pump status. The indices considered in this approach are frequency-, time-, and time-frequency-domain indices. The frequency-domain indices detect changes in the harmonic and subharmonic energy content of the pump flow signal when a suction event is occurring. The time-domain indices detect changes in pump flow pulsatility based on a beat-to-beat analysis of the pump flow and first derivative of pump flow. The time-frequency index can track variations in the standard deviation of the instantaneous frequency of the pump flow signal. These indices are combined in a DA decision system to generate a suction alarm. The proposed system has been tested in simulations and in-vivo experimental tests and produced satisfactory results.**

I. INTRODUCTION

A rotary Left Ventricular Assist Device (LVAD) is essentially a mechanical pump used in patients with congestive heart failure to assist the heart while the patient waits for heart transplantation. Unlike its pulsatile counterpart, rotary LVADs are smaller and consume less energy. The output of a rotary LVAD, however, is sensitive to afterload, i.e, to the hydraulic load it must pump against [1]. In addition, due to the fact that, at least until now, there are no reliable pressure sensors available to detect preload conditions, adaptation to changes in venous return is still a missing factor in many of the control approaches reported in the literature [2], [3]. Therefore, the problem of adjusting pump flow (PF) to accommodate physiologic demand by controlling the pump speed (PS) remains a challenge for rotary LVADs.

Two constraints should be taken into account regarding the pump speed of rotary LVADs. First, the speed should be high enough to avoid regurgitation, i.e, the return of blood from the aorta to the left ventricle through the pump (backflow). Second, the speed should not be so high as to produce suction, i.e, an event that occurs when the pump tries to draw more blood than is available and ventricular collapse may occur, which can lead to cardiac tissue damage. Suction can be defined as the anatomic collapse of the ventricle. It is not only due to over pumping, but it can also be caused by contact between the cannula[1] tip and the left ventricular wall (endocardium). Suction detection is a very important problem in the control of LVADs.

In recent years, several approaches have been used to solve the suction detection problem. These include frequency [4] and time based [5] approaches. Frequency methods are based on an empirical observation that the spectral energy content of signals, such as pump flow and pump current, changes when the patient is experiencing suction [4]. Even though the pump is a continuous flow device, the native impaired ventricle still has pulsatile behavior. As a result, these signals also follow a pulsatile pattern, usually synchronized with the patient's cardiac frequency under normal operation of the LVAD, i.e, not in the speed range that could cause suction to occur.

Time domain techniques are based on a beat-to-beat analysis of pump flow patterns. Usually, these patterns are compared against others in a data base with snapshots of pump flow under different conditions (normal, i.e, no suction, approaching suction, severe suction). A suction detection system based on 11 algorithms that analyze the pump flow patterns for the presence of 6 distinct suction indicators was developed in [5]. Using a window length of 5 seconds, these algorithms extract features from the pump flow signal and compare them against snapshots of pump flow previously stored and classified in a data base by human experts.

Recently, an approach for suction detection in which frequency techniques are supplemented by a time-frequency-based analysis of the pump flow signal was reported [6]. The present paper uses discriminant analysis (DA) to combine these frequency- and time-frequency-based indices with several time domain indices derived from the pump flow wave form. Section 2 describes the features used. Section 3 discusses the DA system, and how all indices were combined using a linear classifier. Section 4 presents the experimental results of an in-vivo study performed in a calf, for which the proposed detector was used. Concluding remarks are presented in Section 5.

II. FEATURE EXTRACTION OF PUMP FLOW

Due to the lack of reliable pressure sensors, current suction detection approaches depend on feature extraction of other available signals, such as Pump Flow (PF), pump current

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[1]The cannula is a plastic rigid tube that connects the ventricle to the inlet of the rotary pump.

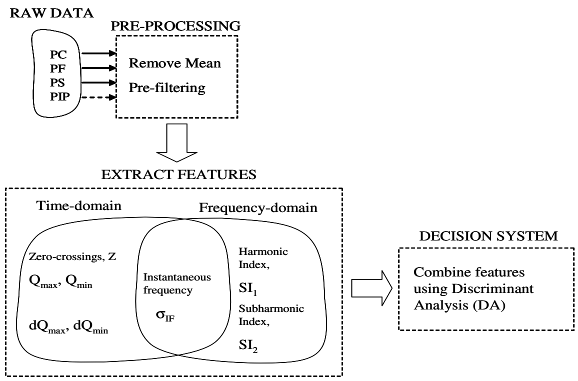

Fig. 1. Suction Detection System Proposed

and pump speed. Figure 1 diagrams the proposed suction detection system. The EXTRACT FEATURES block obtains indices from the pump flow, which allow determination of pump status. In this research, the pump status can be one of the following:

a) No Suction (NS): This is the "normal" condition. Pump Inlet Pressure (PIP) - the pressure at the pump head - is positive and its difference to Left Ventricular Pressure (LVP) is small, i.e, $\Delta P = LVP - PIP \leq$ 10mmHg. Also, PF is a periodic signal;
b) Moderate Suction (MS): In this case, the gradient 10mmHg $< \Delta P \leq$ 25mmHg and some suction is observed. This could be due to intermittent contact between the cannula tip and the left ventricular wall;
c) Severe Suction (SS): In this case PIP presents negative spikes and PF no longer has pulsatile behavior synchronized with the patient's heart rate. The ventricle is completely unloaded and cannot support such negative gradient pressure imposed by the pump. Cardiac tissue damage may occur, and this condition must be avoided.

In the following sections, we describe the frequency, time and time-frequency indices (features) derived from Pump Flow.

A. Frequency based suction indices

Let $Q_P(\omega)$ be the Fourier transform of the pump flow signal, $q_P(t)$, and ω_0 be its fundamental frequency. Consider the frequencies $\omega_1 = \omega_0 - \omega_c$ and $\omega_2 = \omega_0 + \omega_c$, where ω_c is a threshold (in radians) that defines an interval centered at ω_0. The Harmonic index SI_1 is defined as the ratio of the total energy in the fundamental component frequency band to the total energy in the harmonic components frequency band i.e,

$$SI_1 = \frac{\int_{\omega_1}^{\omega_2} |Q_P(\omega)|\, d\omega}{\int_{\omega_2}^{\infty} |Q_P(\omega)|\, d\omega} \tag{1}$$

The Subharmonic index SI_2 is defined as the ratio of the signal's subharmonic energy to the fundamental energy, i.e,

$$SI_2 = \frac{\int_{0}^{\omega_1} |Q_P(\omega)|\, d\omega}{\int_{\omega_1}^{\omega_2} |Q_P(\omega)|\, d\omega} \tag{2}$$

Figure 2 shows results of applying the harmonic and subharmonic indices to in-vivo[2] data. The WorldHeart[3] LVAD was used in this in-vivo study. When a suction event occurs, energy shifts from the fundamental band to the harmonic and subharmonic bands, causing SI_1 to decrease and SI_2 to increase. During severe suction $SI_2 > SI_1$. Note that in this case, the indices have identified correctly the occurrence of severe suction in pump flow for $127 < t < 152$ (see Figure 2, (a)).

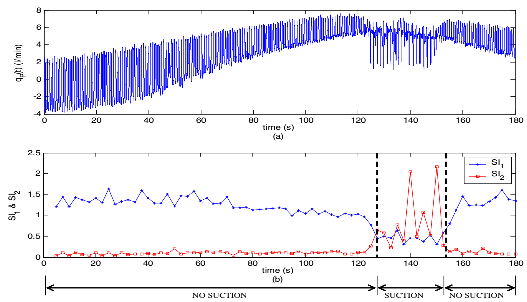

Fig. 2. Simulation result of SI_1 and SI_2 to in-vivo data; (a) Pump Flow, (b) SI_1 and SI_2 as functions of time

B. Time based indices

Let M_i be the supremum of pump flow, $q_P(t)$, in the ith heart beat and m_i be the infimum. Now, consider the sequences $\{M_i\}_{i=1}^{N_1}$ and $\{m_i\}_{i=1}^{N_2}$ of all supremums and infimums of $q_P(t)$ in a given time window ($\Delta t = 5$ seconds), respectively. We define the time features Q_{max} and Q_{min} in the following way:

$$Q_{max} = \frac{1}{N_1}\sum_{i=1}^{N_1} M_i, \qquad Q_{min} = \frac{1}{N_2}\sum_{i=1}^{N_2} m_i \tag{3}$$

Thus, Q_{max} and Q_{min} are the means of the two given sequences above. Note that N_1 does not necessarily equal to N_2, unless the number of heart beats within Δt is an integer. Similarly, we defined dQ_{max} and dQ_{min} as the mean of $\{M_i\}_{i=1}^{N_1}$ and $\{m_i\}_{i=1}^{N_2}$ for the derivative of the pump flow signal, $dq_P(t)/dt$. The time based indices are related to the pump flow pulsatility. When suction is occurring, the pulsatility in the pump flow signal decreases, indicating suction.

C. Time-Frequency based index

The time-frequency algorithm to detect suction events is based on the standard deviation of instantaneous frequency (IF) of pump flow, defined as

$$\sigma_{IF} = \sqrt{\text{var}(\langle\omega\rangle_t^{sp})} \tag{4}$$

In this formulation, the instantaneous frequency is defined as the average frequency at a given time [7], i.e,

$$\langle\omega\rangle_t^{sp} = \frac{\int \omega P_{sp}(\omega, t)\, d\omega}{\int P_{sp}(\omega, t)\, d\omega} \tag{5}$$

[2]Authorized according to the WorldHeart, Inc., IRB DO 01-06002
[3]WorldHeart, Inc., formerly MedQuest, Inc., Salt Lake City, UT

where $P_{sp}(\omega, t)$ is the spectrogram, the squared magnitude of the short-time Fourier transform (STFT). When suction is approached, the standard deviation of instantaneous frequency increases, indicating the occurence of suction, as shown in Figure 3.

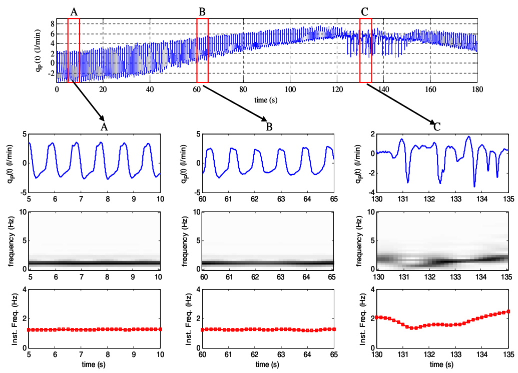

Fig. 3. Spectogram results and Instantaneous frequency of Pump Flow for 3 time windows. A) Normal Operation, B) Moderate Suction, and C) Severe Suction. In each case, panels from the top are PF, Spectrogram of PF, and the Instantaneous frequency of PF $\langle\omega\rangle_t^{sp}$ respectively.

III. THE DECISION SYSTEM

The purpose of the DECISION SYSTEM module in Figure 1 is to combine the several features described in the previous section (SI_1, SI_2, Q_{max}, Q_{min}, dQ_{max}, dQ_{min} and σ_{IF}). Since we have more than two groups (No Suction, Moderate Suction and Severe Suction) to classify a given sample of pump flow, Multiple Discrimiant Analysis (MDA) was used to design a linear classifier. The DA method based on Fisher's approach [8] consists of finding a linear combination of the independent variables (*predictors*) that produce "maximally different" *discriminant scores* across groups [9], [10].

Formally, the general classification problem in DA can be stated as an optimization problem as

$$\begin{aligned} \max \ J(\boldsymbol{\alpha}) &= \frac{\boldsymbol{\alpha}^T \boldsymbol{B}\boldsymbol{\alpha}}{\boldsymbol{\alpha}^T \boldsymbol{W}\boldsymbol{\alpha}} \\ \text{subject to} \quad & \boldsymbol{\alpha}^T \boldsymbol{W}\boldsymbol{\alpha} = 1 \end{aligned} \tag{6}$$

where $\boldsymbol{B}$ and $\boldsymbol{W}$ are the between- and within-group covariance matrices respectively.

Indeed, the problem defined in (6) is an eigenvalue problem, and the optimal α consists of the generalized eigenvectors that correspond to the largest eigenvalues in

$$(\boldsymbol{W}^{-1}\boldsymbol{B} - \lambda \boldsymbol{I})\alpha = 0$$

Note that the columns of the retangular matrix $\boldsymbol{\alpha}$ define the coefficients of the linear combination of the predictors (features), for which the criteria $J(\alpha)$ has a maximum. Since matrix $\boldsymbol{B}$ has rank $(g-1)$ (where g is the number of groups), the matrix $\boldsymbol{W}^{-1}\boldsymbol{B}$ has rank $\max(g-1, p)$ (where p is the number of variables).

IV. EXPERIMENTAL RESULTS

The pump flow signal and other hemodynamic variables were recorded in an in-vivo[2] study performed on a calf. This study was conducted in association with LaunchPoint, LLC (Goleta, CA) and WorldHeart, Inc. The WorldHeart LVAD was used in this experiment and data were sampled at a rate of 500Hz. The in-vivo study had two main goals: to test several control approaches, and to assess suction indices performance. Suction was induced either by overpumping or by clamping the vena cava. The first test method consists of an increase in pump speed, using a ramp profile. Following the test protocol, the speed ramp was applied before any drug administration to the animal, and data recorded in this condition was used as base-line. The second test method, vena cava occlusion, causes less blood to return to the animal's heart. Consequently, less blood is available for the pump to draw, and suction occurs.

The detection system and the discriminant analysis of the data were implemented using MATLAB[4].

The data were previously classified by a human expert into three groups, according to the pump status previously defined in Section II: No Suction (NS), Moderate Suction (MS), and Severe Suction (SS). This classification procedure was based on the analysis of pump flow (PF), pump speed (PS), left ventricular pressure (LVP) and pump inlet pressure (PIP) by the expert, using a 5 seconds long window. That classification process resulted in a data base with 2,485 samples of the pump flow signal. Figure 4 shows the expert classification results.

No Suction	Moderate Suction	Severe Suction
NS	MS	SS
1,756	531	198

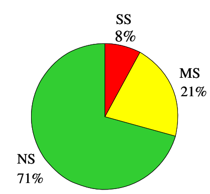

Fig. 4. Expert classification result

Fifty samples drawn from each group were used to train the classifier. The classifier was then applied to the remaining data. In this case, our main goal was to classify the remaining samples (2,335) into one of the three given groups. Table I shows the *hits-and-misses table* (sometimes called a *confusion matrix*) obtained for the discriminant model.

The ratios of the between- to within-group variances are 0.8160 and 0.1840, for α_1 and α_2 respectively. This means that the first canonical variate explains most of the differences between the groups in the data. The discriminant weights and correlations between the variables and discriminant scores are presented in Table II. The disciminant model presents a good result compared to the proportional chance criteria, which is given by $n(p_1^2 + p_2^2 + p_3^2)$. In this case, $p_1 = 1706/2335$, $p_2 = 481/2335$, and $p_3 = 148/2335$, yelding a chance hit rate of $1354/2335 = 58\%$, which is less than the 74% obtained with the discriminant model.

[4]The MathWorks Inc., Natick, MA

TABLE I

CONFUSION MATRIX FOR THE TRAINING SET [a, b]

	NS	MS	SS	Total
NS	35 (70%)	14 (28%)	1 (2%)	50 (100%)
MS	3 (6%)	44 (88%)	3 (6%)	50 (100%)
SS	1 (2%)	11 (22%)	38 (76%)	50 (100%)

[a] Actual groups are in rows, estimated in columns
[b] NS = No Suction, MS = Moderate Suction, and SS = Severe Suction

TABLE II

DISCRIMINANT COEFFICIENTS AND DISCRIMINANT LOADINGS

Feature	**Standardized Discriminant Coefficients**		**Discriminant loadings (correlations)**	
	α_1	α_2	C_1	C_2
SI_1	-3.3952	0.3797	-0.97	0.15
SI_2	0.5733	0.7936	0.72	0.15
Q_{min}	-0.0648	0.1086	-0.18	-0.67
Q_{max}	0.0173	-0.6310	0.15	-0.95
dQ_{min}	0.0006	0.0015	0.16	0.50
dQ_{max}	0.0001	0.0002	-0.40	-0.34
σ_{IF}	2.7342	0.7403	0.87	0.20

Table II shows the standardized discriminant coefficients. These are the weights (also called discriminant functions) used to linearly combine the features, such that the discrimination between groups is maximized. The discriminant loadings are the correlations between each feature and the discriminant scores. Table III shows the group means of the discriminant scores.

Applying the discriminant model to the test set yields the confusion matrix shown in Table IV. Figure 5 shows a plot of the test data in the discriminant score space.

V. DISCUSSION

A new suction detection system based on frequency and time indices combined with a time-frequency index was presented. Table II reveals that the indices SI_1 and σ_{IF} have more weight in the first discriminat function α_1 (Note the absolute value of the discriminant coefficients and the canonical correlations in Table II). As for the second discriminant function α_2, Q_{max} is the more important feature. In Figure 5, a vertical line through -1 in the first discriminant score axis separates SS cases (on the right hand side of that line) from the other groups. The suction detection system presented has been tested in simulations by using in-vivo data. Preliminary analysis has shown that our system was able to detect suction in most cases. This system is planned to be part of a feedback control strategy to automatically adjust pump speed in rotary LVADs.

TABLE III

GROUP MEANS ON DISCRIMINANT FUNCTIONS

	α_1	α_2
NS	-3.1141	-0.0002
MS	-2.0525	-1.6780
SS	0.4769	-0.4026

TABLE IV

CONFUSION MATRIX FOR TEST SET [a, b]

	NS	MS	SS	Total
NS	1,193 (69.9%)	505 (29.6%)	8 (0.5%)	1,706 (100%)
MS	37 (7.7%)	404 (84%)	40 (8.3%)	481 (100%)
SS	1 (0.7%)	20 (13.5%)	127 (85.8%)	148 (100%)

[a] Actual groups are in rows, estimated in columns
[b] NS = No Suction, MS = Moderate Suction, and SS = Severe Suction

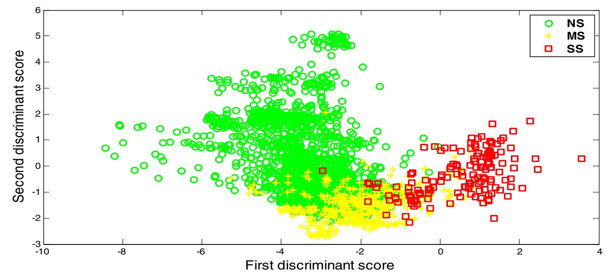

Fig. 5. Plot of test data in discriminant scores space

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