A Gaussian Mixture Model to Detect Suction Events in Rotary Blood Pumps

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***Abstract*— In this paper, we introduce a new suction detection approach based on online learning of a Gaussian Mixture Model (GMM) with constrained parameters to model the reduction in pump flow signals baseline during suction events. A novel three-step methodology is employed: i) signal windowing, ii) GMM based classification and iii) GMM parameter adaptation. More specifically, the first 5 second segment is used for the parameter initialization and the consequent 1 second windows are classified and used for model adaptation. The proposed approach has been tested in simulation (pump flow) signals and satisfactory results have been obtained.**

Keywords—**Implantable rotary blood pump, Left ventricular assist device, Suction detection, Gaussian mixture model.**

I. INTRODUCTION

Left ventricular assist devices (LVADs) which surgically implanted from the left ventricle to the aorta are being increasingly used to treat end-stage heart failure patients [1],[2]. The ultimate aim of LVAD development has been to provide the patient with as close to a normal lifestyle as possible until a donor heart becomes available or, in some cases, until the patients heart recovers [3]. An important challenge facing the increased use of LVADs is the efficient adjustment of the pump flow by regulating the pump speed in order to meet the body requirements for cardiac output and mean arterial pressure. However, one important limitation that must be taken into consideration is to insure that the pump is rotated at a speed below a threshold beyond which the pump attempts to draw more blood from the left ventricle than available causing a phenomenon called suction [4],[5]. This phenomenon, which could cause collapse of the ventricle, is dangerous and needs to be detected and corrected by lowering the pump speed. Hence, the occurrence of suction must be detected in advance, and the pump speed to be reduced before the heart muscle is damaged [6],[7].

To achieve this, a common task is to design a suction detection algorithm extracting some features from available related signals such as pump flow, pump speed, or pump current signals. One major issue when designing a suction detector algorithm is the determination of the pump states. These pump states (or suction states) are usually defined by the experts. The use of two states, suction (S) and no suction (NS) is a common approach adopted in the literature [8]-[10]. However, Ferreira *et al.* [11] and Wang *et al.* [12] made a decision of having three categories of suction patterns: no suction (NS), moderate or approaching suction (MS), and severe suction (SS). In addition, Volkron *et al.* [8] defined five suction states: certainly (NS), most probably (NS), undecided (U), most probably suction (MPS), and suction (S).

The suction detection problem can be simply transferred to the detection of the presence of suction patterns in the available related signals (i.e. pump flow or pump current signals) with high sensitivity and specificity. Several approaches have been proposed to evaluate this issue [2],[5],[6]-[11],[13]-[16]. These approaches are based on empirical observation of certain variables. Thus, some suction indices are based on: (i) time-domain features [8],[10]-[12], (ii) frequency-domain features [10]-[12], and (iii) time-frequency features [10]-[12].

Some of them extract features from the pump flow signal which is one of very few signals that can be easily measured and use powerful pattern recognition algorithms to classify the signal into different pump states [12]. These classifiers vary from simple threshold comparisons [13] to more complex techniques such as classification and regression tree (CART) [9],[16], discriminant analysis (DA) [11], artificial neural networks (ANN) [14] and support vector machines [12]. Most of the suction detection algorithms share two common stages: (i) feature extraction and (ii) classification.

By means of a moving window analysis, features are calculated as suction indices to classify the pump flow status. Several suction detection approaches reported in the literature extract features from a given number of samples of pump flow or other available signals. Vollkron *et al.* [8], Ferreira *et al.* [10],[11] and Wang *et al.* [12] utilize a 5 seconds long window. Karantonis *et al.* [14] makes use of a 6 seconds long window and Morello [15] applies a 2 seconds long window. Then, the classification stage is employed to decide from the calculated features, whether this signal represents a suction state or not.

Based on the aforementioned, it is obvious that when deciding on an algorithm capable of the detection of suction state in pump flow, pump speed, or pump current signals, two important questions need to be answered: (i) What features

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adequately describe suction states for the classifications purposes? (ii) Which machine-learning algorithm must be used?

In this paper, we propose a novel three-step methodology (Fig. 1) for suction events detection in pump flow signals based on a constrained GMM for online estimation of both signals baseline and signals baseline reduction during suction events. This methodology is advantageous due to its simplicity compared to other methods which use a large number of features and its ability to operate in real time.

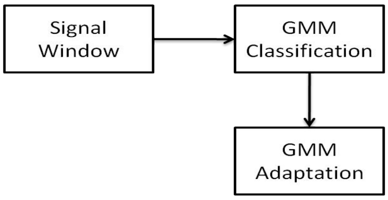


Fig. 1. The proposed methodology for suction event detection.

II. Dataset

Simulation data and specifically 10 pump flow signals with suction events (approximately 46 minutes in total duration) are collected from VAD-Heart Simulation Platform-a Hybrid Simulator [17] which enables the specialists to simulate the behaviour of a patients circulatory system with connected a real assist device (e.g. nonpulsatile blood pump). The Hybrid Simulator consists of two main parts, physical part and numerical part [17]. The physical part (presented in Fig. 2) comprises of four impedance transformers [18] enabling a connection of real assist device to the numerical circulatory system. The movable table presented in the front of the physical part allows to manipulate the tested VAD e.g. in order to change the working static pressure.

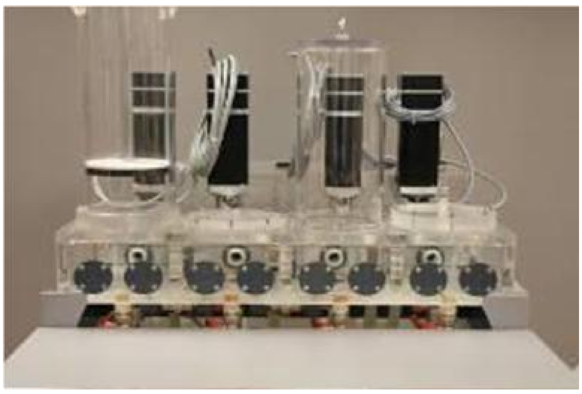
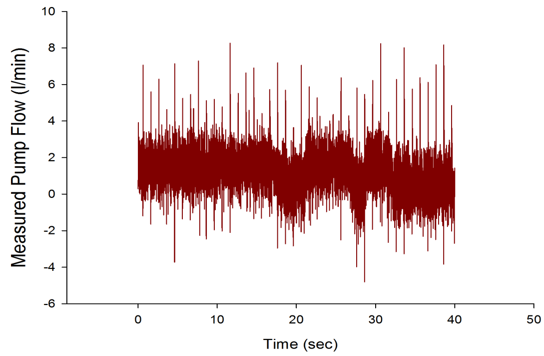


Fig. 2. Physical Part of the VAD-Heart Simulation Platform.

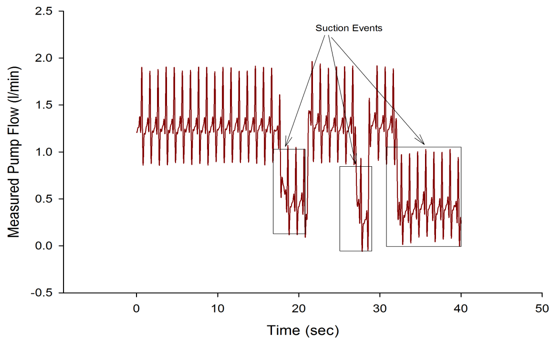
The numerical part of the VAD-Heart Simulation Platform is realized by two computer systems: a real-time computer with special operation system installed (for acquisition, control and calculation operations), and a "host" computer playing the role of the User Interface (data presentations, setting the circulatory model parameters etc.). A software, running on the real-time computer, simulates (in real-time) a numerical circulatory system [19] whereas an User Interface enables setting the numerical circulatory system parameters, data visualization and storing etc. In this case the "real-time software" was adjusted to realize a parallel assistance by means of a physical, continuous, rotary blood pump. The basic mathematical model (described in [19]) of the circulatory system is based on one compartment windkessel model for each functional block of the circulatory system (arterial systemic, arterial venous, arterial pulmonary and venous pulmonary blocks). The left and right heart model are based on a time-varying elastance model.

III. Methodolgy

A segment of a pump flow signal is displayed in Fig. 3(a). In order to indicate more clearly the regions of interest where suction events occur, a lowpass filtered version of the same signal is given in Fig. 3(b). In the filtered signal is clearly depicted that suction events as those are given by the simulator, are related to a rapid degradation of the signal baseline.



(a)



(b)

Fig. 3. a) Segment of original measured pump flow, and b) filtered version of signal where suction events are highlighted.

Therefore, our methodology aims on tracking the baseline of the signal and detection those rapid baseline degradations related to suction events. In order to achieve that we followed the methodology shown in Fig. 1. A similar methodology was adopted by Rigas *et al.* in [20], where physiological stress events were detected in heart rate signal, which demonstrated a rapid increase during those events.

The methodology as depicted in Fig. 1 consists of three steps: i) Signal windowing, ii) GMM classification and iii) GMM adaptation.

A. Signal windowing

Our methodology calculates the average of a 1-sec window:

$$x_k = \frac{1}{FS} \sum_{i=(k-1)\cdot FS+1}^{k\cdot FS} y_i. \quad (1)$$

where x_k is the average of the k^{th} window, FS is the sampling frequency, and y_i the input signal. The length of one second (500 samples) is sufficient to ensure that the estimation of the signal's baseline for the given moment is accurate enough. The resulting x_k is the input for the following steps of our methodology.

B. GMM Classification

Above the modeling is performed using a GMM with two components. However, instead of using two indendent parameters for the means of the two components, one for the non suction signal and one for the suction signal, we consider that the mean of the second mixture (suction signal) is given as the mean of the first component with the addition of a constant. This constant is a negative number which reflects the average degradation of the signal occured in suction events. Using this assumption, the model describes more accurately the nature of the signal in hand and can be formaly described as:

$$x_i \sim \begin{cases} N(x_i;\mu_1,\sigma_1), & \text{for non suction} \\ N(x_i,\mu_1+\delta,\sigma_2), & \text{for suction} \end{cases}. \quad (2)$$

The mixing probability of each component is defined as π_1 and π_2 and it is considered constant. σ_1, and σ_2 are also constants as well as δ in our experiments is also considered as fixed and estimated from the initial training of the model. Those parameters are obtained from an initial training of the model.

Using the model described above we classify the x_k as a suction or non-suction sample according to the component having the highest likelihood.

C. GMM Adaptation

Using each new sample x_k we adapt the model's parameters using an online method. The batch adapation of the parameters is based on the Expectation-Maximization (EM) method. The EM estimation of the ML parameters of the model is described in [20] and for the μ_1 the update formula is given as:

$$\mu_1 = \frac{(\sum_i w_{i1}x_i/\sigma_1^2 + \sum_i w_{i2}x_i/\sigma_2^2) - \sum_i w_{i2}\delta/\sigma_2^2}{(\sum_i w_{i1}/\sigma_1^2 + \sum_i w_{i2}/\sigma_2^2)}, \quad (3)$$

where w_{i1} and w_{i2} are given as:

$$w_{i1} = \frac{\pi_1 N(x_i;\mu_1,\sigma_1)}{\pi_1 N(x_i;\mu_1,\sigma_1) + \pi_2 N(x_i;\mu_1+\delta,\sigma_2)}, \quad (4)$$

$$w_{i2} = \frac{\pi_2 N(x_i;\mu_1+\delta,\sigma_2)}{\pi_1 N(x_i;\mu_1,\sigma_1) + \pi_2 N(x_i;\mu_1+\delta,\sigma_2)}. \quad (5)$$

In our experiments σ_1 and σ_2 are considered equal and fixed, where their values were estimated from the training of the model. Eq. (3), given $\sigma_1 = \sigma_2 = \sigma$, can be rewritten as:

$$\mu_1 = x_i - w_{i2}\delta. \quad (6)$$

In order to adapt the mean of the GMM on the signal we used the following online update formula for μ_1:

$$\mu_1^i = (1-\alpha)\cdot\mu_1^{i-1} + \alpha\cdot(x_i - w_{i2}). \quad (7)$$

In our experiments α was set to 0.1.

IV. Results

The parameter δ for the GMM model are initially estimated using the pump flow simulation dataset. For each signal, signal segments with the same baseline are manually extracted. Then for each segment the average of the suction and non-suction signal was calculated. The difference of those averages provided an estimation of δ. The estimation from our dataset was -0.5.

Then for each of the 10 signals in the dataset the methodology was applied. The first 5 seconds of the signal were used for the estimation of an initial mean μ_i and the standard deviation σ. Then for each 1-sec window the classification and adaptation steps were applied. The probability of suction as provided by our methodology is depicted in Fig. 4. In Fig. 4 the ground truth for the first signal is also provided, for comparison purposes. The correlation of the estimation and ground truth for the specific segment was 0.84.

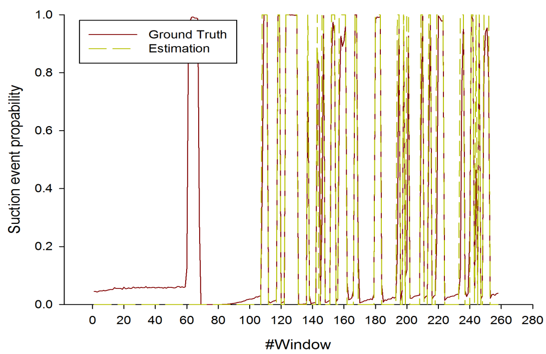


Fig. 4. Suction ground truth and estimation.

In order to quantify the performance of our methodology the ROC curve for the detection of suction in the 10 signals of our dataset is given in Fig. 5. The area under curve (AUC) was 0.97.

The confusion matrix, sensitivities, specificities and the total accuracy are given in Table I. Signal windows were classified as suction events when the GMM component corresponding to suction had probability larger the 0.5, otherwise they were classified as non-suction.

TABLE II

SUCTION DETECTION METHODS PRESENTED IN THE LITERATURE.

Author(s)	Year	Classification	Pump or suction states	Results
Ferreira et al. [10]	2006	Thresholding function	I. NS II. SS	For SS detection Sensitivity:88% Specificity:95%
Ferreira et al. [11]	2006	Discriminant analysis	I. NS II. MS III. SS	NS Accuracy: 69.9% MS Accuracy: 84% SS Accuracy: 85.8% Total Accuracy: 73.8%
Vollkron *et al.* [8]	2006	Thresholding function	I. NS II. MS III. MPS IV. SS V. U	False positive rate:0.42% SS Accuracy: 85.8% False negative rate: 1.5%
Karantonis et al. [16]	2007	Regression tree (CART)	I. NS II. SS	For SS detection Sensitivity:99.11% Specificity:98.76%
Karantonis et al. [14]	2008	Artificial Neural Networks (ANN)	I. NS II. SS	For SS detection Sensitivity: 98.54% Specificity:99.26%
Wang *et al.* [12]	2011	Lagrangian Support Vector Machines (LSVMs)	I. NS II. MS III. SS	NS Accuracy: 69.9% MS Accuracy: 84% SS Accuracy: 85.8% Total Accuracy: 73.8%
Tzallas et al.	2012	Gaussian Mixture Model (GMM)	I. NS II. SS	For SS detection Sensitivity: 81% Specificity:88%

No Suction (NS), Moderate Suction (MS), Most probably Suction (MPS), Severe Suction (SS), Undecided (U).

TABLE I

CONFUSION MATRIX, SENSITIVITY AND SPECIFICITY FOR EACH CLASS AND TOTAL ACCURACY FOR THE CLASSIFICATION OF SUCTION EVENTS USING THE GMM ADAPTATION MODEL.

Suction		
Confusion Matrix		
	Non Suction	Suction
Classified as Non Suction	1904	71
Classified as Suction	117	510
Sensitivity	0.96	0.81
Specificity	0.94	0.88
Overall Accuracy	**0.93**	

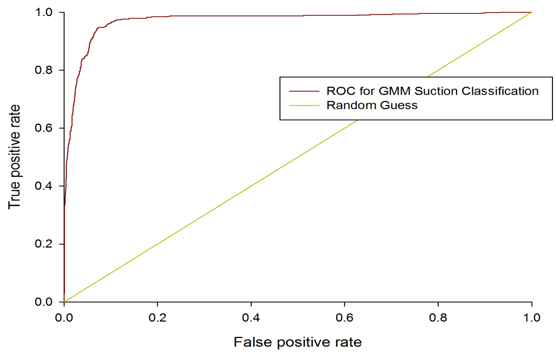


Fig. 5. ROC curve for the GMM classification (AUC=0.97).

V. DISCUSSION

We proposed a methodogy for suction event detection based on a constrained Gaussian mixture model for online estimation of both signal's baseline and signal's baseline reduction during suction events. Our methodology consists of three steps: i) signal windowing, ii) GMM based classification and iii) GMM parameter adaptation. For each new signal, the first 5 second segment is used for parameter initialization and the consequent 1 second windows are classified and used for model adaptation. The ROC curve (Fig. 5) for suction detection had a high AUC (0.97) and the classification provided accuracy of 0.93.

The literature presents various methods which applied to suction detection in rotary blood pump systems. The majority of the related works adressed mainly the feature extraction from the pump flow signals and the use of pattern recognition techniques to classify the signal into different states and detect suction events. A comparison of our methodology with other detection techniques given in the literature is quite difficult. The reason behind this is that these studies consider different rotary blood pumps and make use of nonstandard and different databases, some of them not available publicly. Although a direct comparison is not feasible, in Table II, we present a comparison of the methods reported in the literature.

VI. CONCLUSIONS

A methodology for suction event detection was presented based on online learning of a Gaussian mixture model with constrained parameters to model the reduction in signal's baseline during suction events. The proposed methodology gave very good results. The advantage of the proposed methodology is its simplicity compared to other methods using a large number of features, the ability to apply this method in real time applications, and the very good results comparable to methods proposed in the literature.

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