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Modeling and simulation of speed selection on left ventricular assist devices

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ABSTRACT

The control problem for LVADs is to set pump speed such that cardiac output and pressure perfusion are within acceptable physiological ranges. However, current technology of LVADs cannot provide for a closed-loop control scheme that can make adjustments based on the patient's level of activity. In this context, the SensorART Speed Selection Module (SSM) integrates various hardware and software components in order to improve the quality of the patients' treatment and the workflow of the specialists. It enables specialists to better understand the patient–device interactions, and improve their knowledge. The SensorART SSM includes two tools of the Specialist Decision Support System (SDSS); namely the Suction Detection Tool and the Speed Selection Tool. A VAD Heart Simulation Platform (VHSP) is also part of the system. The VHSP enables specialists to simulate the behavior of a patient's circulatory system, using different LVAD types and functional parameters. The SDSS is a web-based application that offers specialists with a plethora of tools for monitoring, designing the best therapy plan, analyzing data, extracting new knowledge and making informative decisions. In this paper, two of these tools, the Suction Detection Tool and Speed Selection Tool are presented. The former allows the analysis of the simulations sessions from the VHSP and the identification of issues related to suction phenomenon with high accuracy 93%. The latter provides the specialists with a powerful support in their attempt to effectively plan the treatment strategy. It allows them to draw conclusions about the most appropriate pump speed settings. Preliminary assessments connecting the Suction Detection Tool to the VHSP are presented in this paper.

1. Introduction

Heart failure (HF) is affecting millions of people in Western Countries every year, and is characterized by impaired ventricular performance, exercise intolerance, and shortened life expectancy. Despite significant advancements in drug therapy, mortality of the disease remains excessively high, as heart transplantation is the only accepted method to treat severe cases. Unfortunately, heart transplantation is limited by the number of donor organs, and therefore Left Ventricular Assist Device (LVAD) support is nowadays considered an alternative for many cases of end-stage heart failure [1]. In addition, two other roles have recently appeared: "bridge to recovery" and "destination therapy" which guarantee an acceptable quality of life.

As the patient recovers and his level of activity increases, the body's demand for cardiac output increases. The control problem for LVADs is to set the pump speed such that cardiac output (pump

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flow) and pressure perfusion are within acceptable physiological ranges. Care must be taken to ensure that the speed is not set too high or too low. A speed that is too high can create negative pressure in the ventricle, i.e. suction. If the speed is too slow, the unloading of the left ventricle may be insufficient. Left Ventricular (LV) filling pressure and pulmonary artery pressure will remain high, cardiac output could be too low, and the patient will probably experience persistent heart failure symptoms. Because of the limited available information, specific methods have been developed for determining an optimal pump speed based on the characteristics of the pump motor (e.g. current, voltage, and speed) [2–5]. In addition, similar methods try to infer the hemodynamic and circulatory parameters of a patient and consequently the pump speed without the use of implantable sensors [6–8]. However, these estimations and methods are reliable only in a relatively narrow range of pump parameters. In addition, a solution to maximize cardiac output while operating the pump at a safe speed is to operate the pump at a speed just below suction. The drawback to this solution is that a pump speed that does not cause suction may still have adverse effects on other physiological parameters [2].

Furthermore, other approaches have been developed that provide control of the pump speed based on a safe or optimal range of a certain systemic vascular resistance (SVR) [6–10]. However, these may cause suction phenomena, if the SVR varies due to changes in the physiological state of the patient. In addition, other parameters such as the heart rate have been employed as control input. As one part of the circulation regulatory system, the heart rate is an indicator of blood flow demand of the body. However, heart failure patients may suffer from brady- or tachy arrhythmias, their heart rate (HR) may be induced by permanent pacing, and the majority of them are taking beta-adrenergic receptor blockers [11]. All these factors make the relationship between changes in HR and changes in cardiac output requirements for adaptation to exercise, less predictable and consistent. In the provided experiment, the controller adjusted the pump speed in response to increasing or decreasing heart rate in a linear relationship. However, this method does not take into account the change in SVR. From rest to exercise, there is a dramatic decrease in SVR accompanying the increase in heart rate. For the case of heart failure where the heart is not pumping effectively, the change in SVR is a major mechanism to generate the desired cardiac output. In addition, an improved method was presented in [12] that incorporates the HR and the SVR, and responds to the physiological changes of the body instantaneously based on the baroreflex, the built in cardiovascular regulation system. The HR was inferred from pump current and the systemic vascular resistance was estimated from blood flow and blood pressure. In [13] the constraints on cardiac output, left atrial pressure, and arterial pressure are presented. A penalty function is assigned to each hemodynamic variable, and a mathematical model of the LVAD and cardiovascular system is used to map the penalty functions as functions of the hemodynamic parameters, to penalty functions as functions of the pump speed. Forming a weighted sum, the penalties for the different variables are combined and the best set of pump speeds is determined by minimizing the combined penalty functions using different sets of weights. The resulting set of best pump speeds forms the Non-Inferior Set (NIS).

In this context, the SensorART Speed Selection Module (SSM) provides a set of valuable tools to the specialists in order to investigate important hemodynamic variables and dynamically changing circulatory parameters that impose particular difficulties in the control problem of LVADs and the determination of an optimal operation. In a critical care setting, the desired operating point of the LVAD may be determined by a specialist or technical personnel and is adjusted to provide more or less cardiac output depending on the status of the patient. However, when the patient leaves the critical care setting a clinician is no longer readily available, and the device must provide adequate cardiac output to sustain the patient's level of activity without clinical supervision. Particular care has to be taken to ensure that the speed is not set too high (creating suction) or too low (causing blood to flow back into the pump). Thus, the SensorART SSM incorporates different hardware and software components in order to enable specialists to better understand the patient–device interactions, and safely explore new knowledge. The VAD Heart Simulation Platform (VHSP) allows specialists to create different simulation sessions based on a patient's hemodynamic condition to be reproduced. The main novelty of the proposed study is the development of a new integrated solution consisting of hardware and software tools for building up and processing circulatory models according to the needs of patient who suffer from heart failure. It is a first attempt to gain insight into heart assist problems in order to improve the quality of the patients' treatment and the workflow of the specialists. It will be eventually enable specialists to better understand the patient–device interactions, and improve their knowledge about this process. The suction schema is based on hybrid and numerical simulator with main focus on Circulite pump. Certainly, the validation of the suction detection module is not complete and does not cover all the possibilities of suction in general, but the present study is a first attempt in evaluating the suction detection module in specific condition and then to test the overall behavior of it in the speed selection tool.

2. Materials and methods

The SensorART SSM consists of an integrated hardware and software solution for building up and processing circulatory models according to the user needs-specially when heart assist simulation problems are concerned. It consists of three components (Fig. 1):

- the VAD Heart Simulation Platform,
- the Speed Selection Tool and
- the Suction Detection Tool.

2.1. VAD heart simulation platform

The VAD Heart Simulation Platform (VHSP) is a representation of the cardiovascular system. It can be both a computational standalone simulator, or a hybrid (numerical-hydraulic) simulator. The computational simulator is made by a cardiovascular model plus a numerical representation of the VAD. It is a tool devoted to clinical environment, therefore it can be run on a laptop with a low execution time.

The hybrid simulator is an extended and more powerful version of the computational simulator. It shares the same cardiovascular model but in addition it includes also an hydraulic module. In comparison to the computational simulator, the hybrid simulator permits the user to physically connect and test a real VAD in real time.

2.1.1. Computational simulator

The computational simulator is based on a lumped parameter model providing the representation of the following circulatory branches: ascending and descending aorta, systemic circulation (split into upper body, kidneys, abdomen and lower limbs), superior and inferior vena cava and pulmonary circulation [14,15]. Left and right atria are reproduced by two compliances, left and right ventricles are represented according to the time varying elastance model [16–18]. The numerical simulator has some additional modules that can be activated if needed: baroreflex control, liquid infusion module, interventricular septum representation, ECG activity, etc.

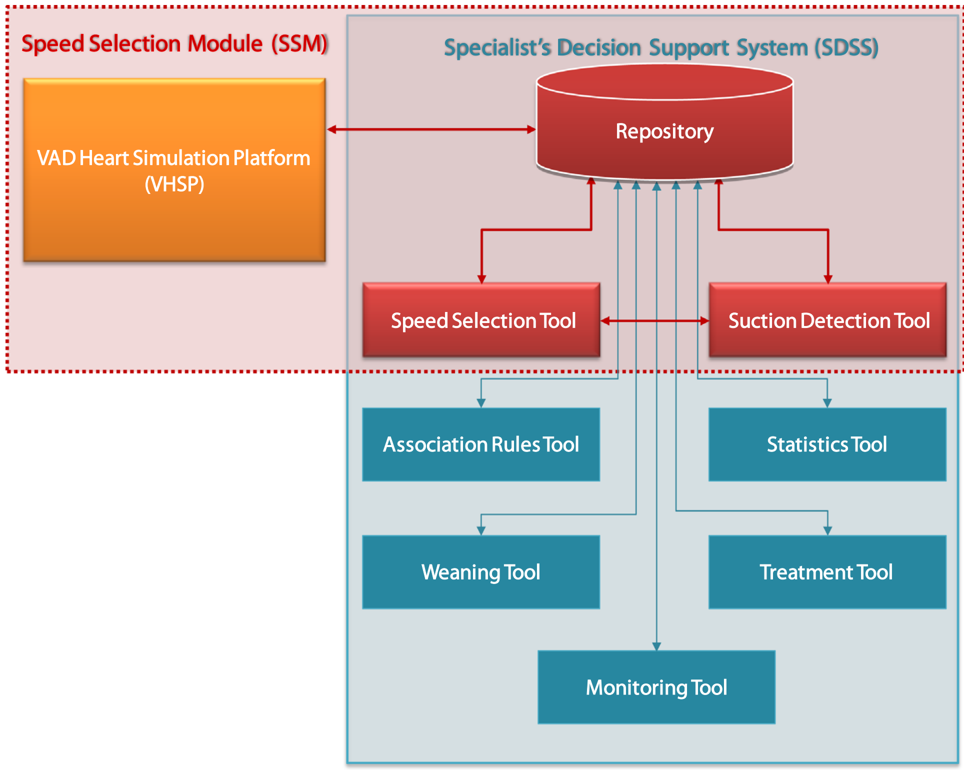


Fig. 1. The Architecture of SensorART Speed Selection Module (SSM) which consists of two main modules: the VAD Heart Simulation Platform (VHSP) and two tools of the Specialist Decision Support System (SDSS): the Speed Selection Tool and the Suction Detection Tool.

A dedicated module was developed for the simulation of different pathologies that usually affect patients assisted by a left ventricular assist device as: ischemic/dilated/hypertrophic cardiomyopathy, right heart failure, interventricular septum failure, aortic regurgitation, aortic stenosis, atherosclerosis, systemic hypertension, pulmonary hypertension. Each of these pathologies (or a combination of them) as well as a level of severity can be selected on demand on the simulator by means of a dedicated user interface. The hemodynamics resulting from the selected physiopathological condition, in terms of pressure, flow and volume waveforms can be plotted and saved for further processing.

In addition, a separate module is devoted to the representation of LVAD as CircuLite's Synergy Micropump, HeartWare [19] and HeartMate II. For the present application the CircuLite's Synergy Micropump was used. The pump model provides the representation of the relationship between pressure drop across the pump and the flow provided for different rotational speeds (from 20,000 to 30,000 rpm). The pump model is connected to the cardiovascular simulator by means of an inflow and an outflow cannula (represented as RLC circuits), one placed in the left atrium and the other in the ascending aorta.

A specific effort was devoted to the reproduction of suction events occurring at the inflow cannula. If pressure in the left atrium drops, because of a low venous return or because of an excessive pump blood drainage, suction may occur between the inflow cannula and the atrial wall. To reproduce such phenomenon the left atrium was represented as follows: for positive values of transmural pressure the left atrium behaves as a passive compliance, for negative values of transmural pressure, the pressure–volume relationship of the atrium is described by an asymptotic curve. If the left atrial pressure drops, the inflow cannula resistance progressively increases to simulate the adhesion of the tip to the atrial wall. As a consequence, the pressure drop across the pump increases and the blood provided by the assist device is reduced. The validation of the computational model was previously conducted using clinical data as reported in [17–19].

2.1.2. Hybrid simulator

The hybrid simulator includes the computational model described above with the exception of the pump models as in this case the real pump can be connected directly to the simulator itself. The hybrid simulator is composed of four *impedance transformers* as illustrated in Fig. 2. Each impedance transformer is devoted to the real time connection between the computational and the hydraulic parts, in four different sites of the cardiovascular model. Four gear pumps are assembled with servomotors and tacho-generators, rigidly fixed to the stiff rod being part of the set-up rack. On the same rack two hydraulic blocks are elastically suspended: a fluid tank and a four-chamber hydraulic section devoted to four impedance transformers. Pressure sensors are mounted in the middle of the bottom of each chamber. A system of chamber openings makes possible connecting the physical LVADs and hydro-pneumatic capacitors as well [18–20]. As in this paper the Circulite Synergy Micropump was studied, two of the four impedance transformers were used, one for the real time connection with the left atrium and one for the real time connection with the ascending aorta [14].The connection between the hydraulic and the computational parts was arranged by two computer modules: a "real-time" module governing time critical functionalities (for acquisition, control and equation solving operations), and a "host" computer playing the role of the User Interface (data presentations, setting the circulatory model parameters, etc.). The validation of the hybrid simulator was performed using experimental data as reported in [14].

2.2. Speed selection tool

The Speed Selection Tool is a web-based component of the SensorART SDSS, and part of the SensorART SSM. It is available through a standard web browser, and proposes adjustments to pump speed settings, according to the required cardiac output and pressure perfusion.

Setting the pump speed of the VAD is an important parameter in order to ensure the patient's quality of life. The Speed Selection Tool

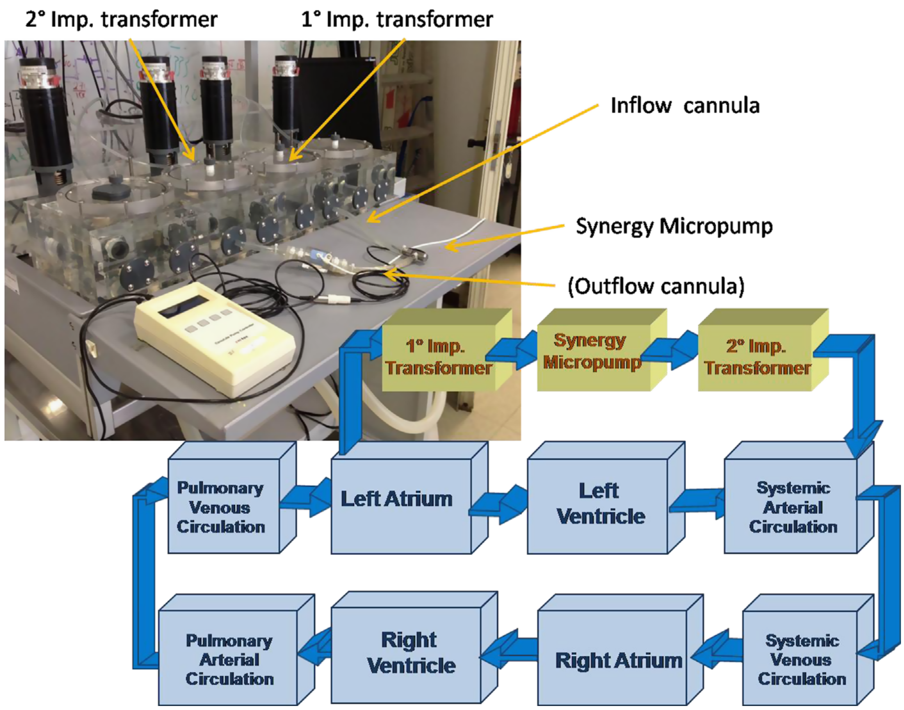


Fig. 2. Block diagram of the cardiovascular simulator and its connection with the hydraulic part. The picture in the left upper corner evidences the hydraulic structure of the impedance transformer and its connection with the Circulite Synergy Micropump.

allows for the submission of simulation parameters to the VHSP, the investigation of the potential effect on important hemodynamic variables (such as cardiac output and arterial pressure), and the processing of the resulting simulation sessions (Fig. 3). Through a set of web services, the availability of the VHSP is established, and requests for simulation sessions can be submitted. Each request is specified through a set of predefined variables. The dataset is composed of cardiac and circulatory variables, and other parameters which are important to obtain the specific object's patho-physiological condition (Table 1).

The output data (simulation data produced by VHSP) which are also continuously recorded with rate 500 samples/s rate and duration up to half an hour, are as follows:

- Left atrial pressure (PCWP) (mmHg).
- Left ventricular pressure (mmHg).
- Aortic pressure (BP) (mmHg).
- VAD flow (l/min) – measured by an external flow meter or by the VHSP.
- Heart rate (l/min).
- Total cardiac output (l/min).
- Pump speed in RPM.

The speed selection process is based on the flow chart given in Fig. 4 which has been introduced by specialists. It depends on the successful determination of suction events, and the calculation of an optimal speed based on the optimal cardiac output.

2.3. Suction detection tool

The Suction Detection Tool is the main component of the SensorART SSM. 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. One important limitation is the need 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 suction phenomenon. It may cause collapse of the ventricle, it is dangerous and needs to be detected and corrected by lowering the pump speed. Hence, suction detection is a very important issue in the control of LVADs. 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 detection algorithm is the determination of the pump states. The specialists usually define pump states (or suction states). The use of two states, Suction (S) and Non Suction (NS) is a common approach adopted in the literature [20–22]. However, several approaches that have used three or five suction states are also reported [20,23,24]. The suction detection problem can be simply transferred to the detection of the presence of suction events in the available related signals such as pump flow or pump current signals with high sensitivity and specificity. Numerous approaches have been proposed to address this issue [5,20–29] following two common stages: (i) feature extraction (based on time-domain [20,22–24], frequency-domain [22–24] and time-frequency domain features [22–24]) and (ii) classification (using regression trees [21], discriminant analysis [23], artificial neural networks [28] and support vector machines [24,30]).

However, in our case, the study of simulation signals revealed no differences in frequency and time domain characteristics of the signal for two pump (S and NS) states. The only significant difference was in the baseline of the pump flow signal, which is reduced in suction states. For this reason, we applied a novel suction detector that is based on the recognition of the sudden decreases in signal's baseline [31,32]. This methodology is based on online estimation of a Gaussian Mixture Model (GMM) with two mixtures corresponding to NS and S classes and it consists of three steps: (i) Signal windowing, (ii) GMM based classification, and (iii) GMM parameter adaptation [31].

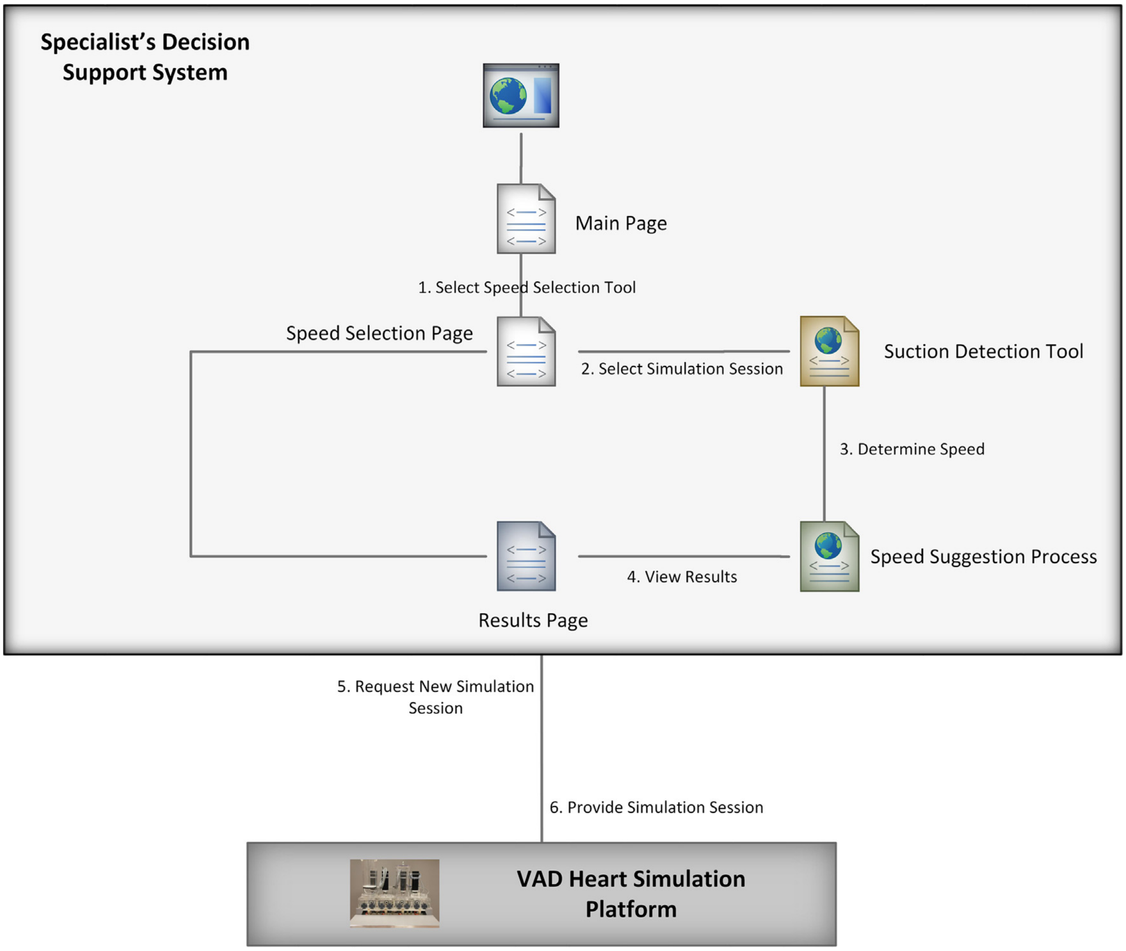


Fig. 3. Internal connectivity of VAD Heart Simulation Platform (VHSP) and Specialist Decision Support System (SDSS).

2.3.1. *Signal windowing*

The average of a sec window is calculated:

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

where x_k is the average of the kth window, FS is the sampling frequency, and y_i the input pump flow signal. The resulting x_k is the input for the following steps of the suction detection methodology.

2.3.2. *GMM based classification*

Above the modeling is performed using a GMM with two components. However, instead of using two independent parameters for the means of the two components, one for the NS signal (μ_B) and one for the S signal (μ_s), we consider that the mean of the second mixture (S signal) is given as the mean of the first component with the addition of a constant D ($\mu_S = \mu_B + D$). This constant is a negative number which reflects the average degradation of the signal occurred in S events. Using this assumption, the model describes more accurately the nature of the signal in hand and can be formally described as

$$x_i \sim \begin{cases} p_B \cdot N(x_i; \mu_B, \sigma_B) & \text{for NS.} \\ p_s \cdot N(x_i; \mu_S, \sigma_S) & \text{for S.} \end{cases} \tag{2}$$

The mixing probability of each component defined as p_B and p_s, is considered constant. Standard deviations σ_B and σ_S are also considered as constants. Those parameters are obtained from an initial training of the model. Using the model described above we classify the x_k as a S or NS sample according to the component having the highest likelihood.

2.3.3. *GMM adaptation*

For each new sample x_i the adaptation step includes the μ_B parameter update using an online learning GMM approach:

$$\mu_B^i = a \cdot \mu_B^{i-1} + (1-a) \cdot (x_i - p_s \cdot D), \tag{3}$$

$$p_s = N(x_i; \mu_S, \sigma_S). \tag{4}$$

where a learning constant $a=0.1$. This methodology is advantageous due to its simplicity compared to other methods, which uses a large number of features and its ability to operate in real time [31,32]. An exemplary segment of a pump flow signal is displayed in Fig. 5(a). In order to indicate more clearly the regions of interest where suction events occur, a low-pass filtered version of the same signal is given in Fig. 5(b). In the filtered signal is clearly depicted that suction events as the simulator gives those, are related to a rapid degradation of the signal baseline.

3. Results

In order to assess the SensorART SSM, a set of simulation sessions was created with the aim to initially validate the Suction Detection Tool, which provides the core functionality in the overall

Table 1
The list of parameters which are obtained for a specific object patho-physiological condition.

Web service parameter name	Range	Unit	Description
username	n/a	n/a	Name of SDSS user (login/nickname)
id	> 0	n/a	Timestamp
describe	n/a	n/a	Some description for VHSP if necessary
weight	> 0	kg	Patient's weight
bsa	> 0	n/a	Body surface area
rpm	0-30000	rpm	Pump SPEED
pump	n/a	n/a	Type of the pump
diameter	> 0	mm	End diastolic ventricular diameter
cannula	0–1	n/a	Cannulation type: 0-atrial, 1-apical
hr	0–200	1/min	Heart rate
co	0–8	l/min	Cardiac output
bpm	0–250	mmHg	Mean blood pressure
bpm ax	0–250	mmHg	Max blood pressure
bpm in	0–250	mmHg	Min blood pressure
pcwpm	0–50	mmHg	Wedge pressure (mean)
papm	0–50	mmHg	Mean pulmonary arterial pressure
cvpm	0–30	mmHg	Mean Central Venous Pressure
pq	50–240	ms	ECG → PQ duration
qrs	60–200	ms	ECG → QRS duration
qt	250–550	ms	ECG → QT duration
mv	0–4	n/a	Mitral valve regurgitation severity
av	0–4	n/a	Aortic valve regurgitation severity
avsten	10–200	mmHg	Aortic valve stenosis-gradient of mmHg
tv	0–4	n/a	Tricuspid valve regurgitation severity
lvesv	0–400	ml	Left ventricular end systolic volume
lvedv	0–350	ml	Left ventricular end diastolic volume
disease	n/a	n/a	Disease
dur	0–30	min	Duration of simulation

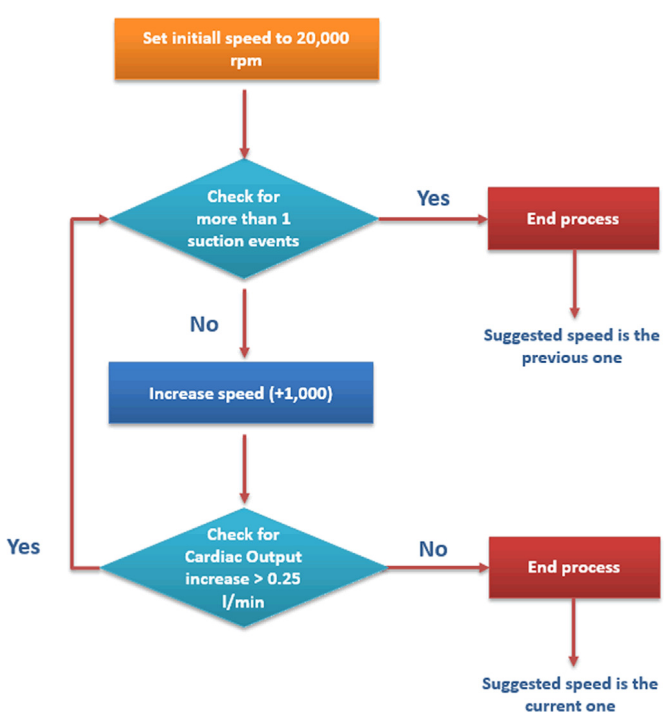


Fig. 4. The flowchart of the Speed Selection Process.

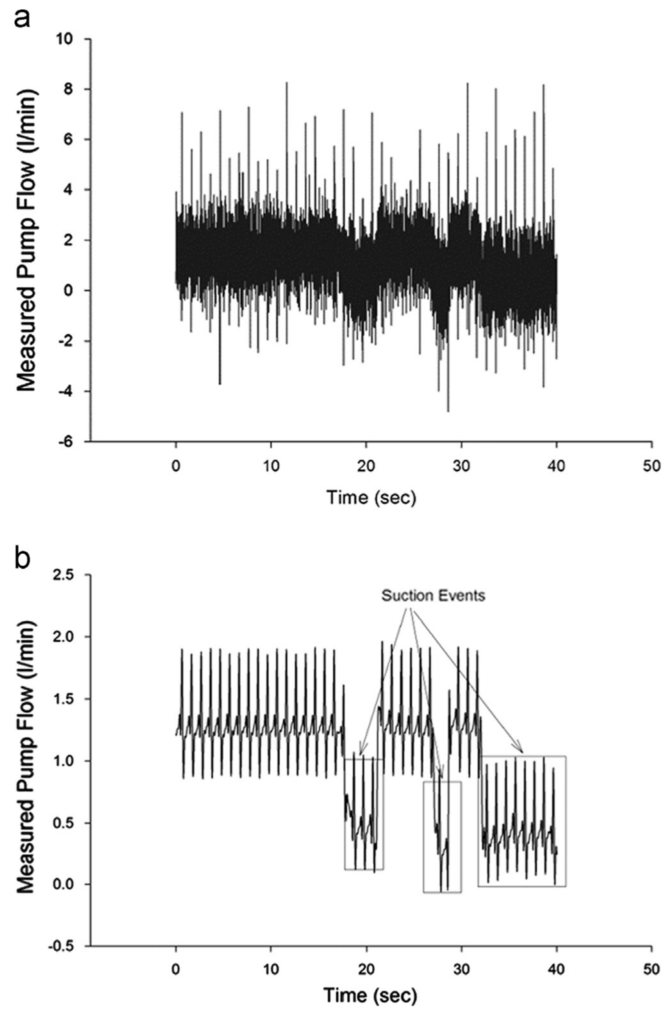


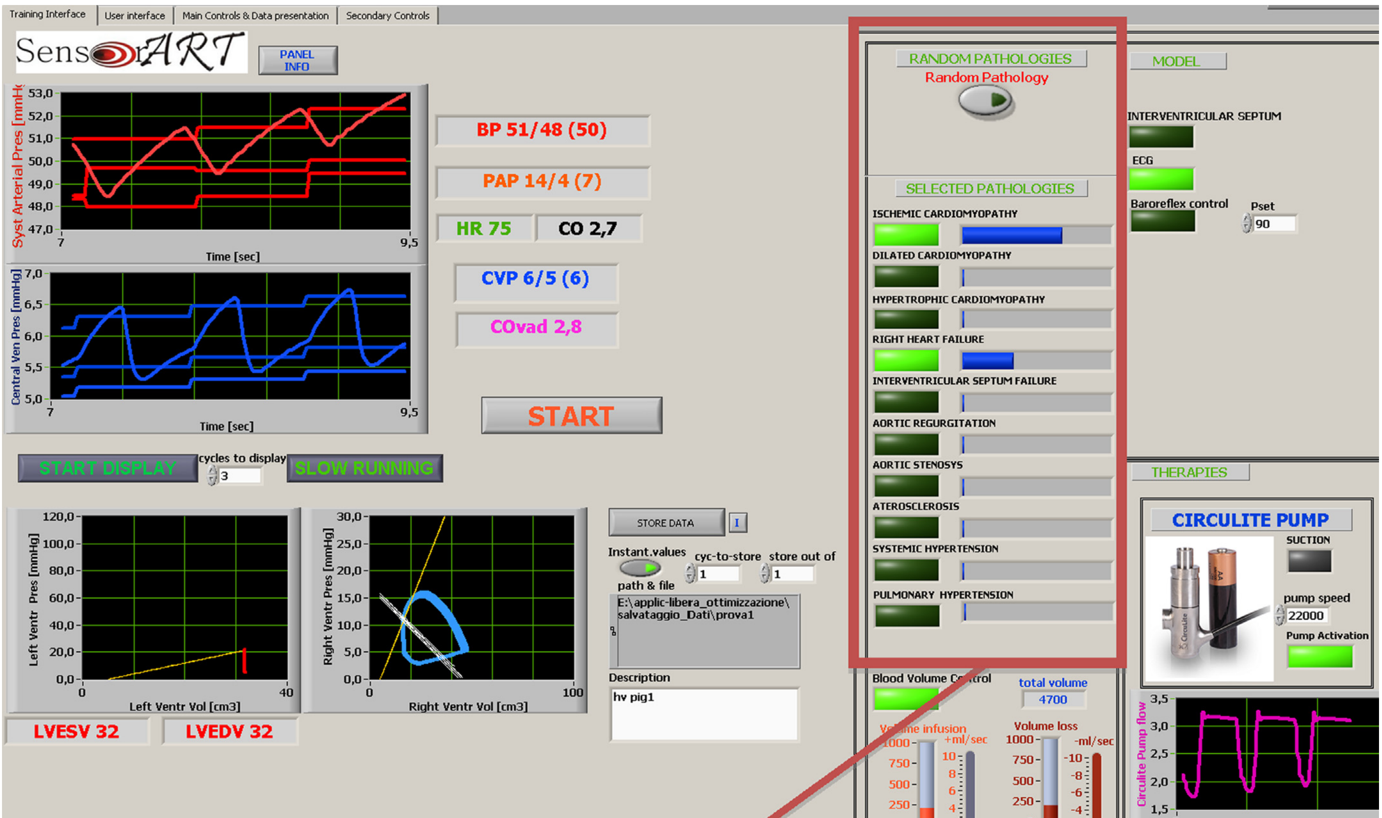
Fig. 5. (a) Segment of original measured pump flow, and (b) filtered version of signal where suction events are highlighted [29].

speed selection process (Fig. 4). Through the VAD Heart Simulation, two different datasets were employed:

- **Dataset I:** 10 pump flow signals with suction events of approximately 46 min in total duration were created from hybrid cardiovascular simulator which enables the specialists to simulate the behavior of a patient's circulatory system with connected a real assist device (e.g. non-pulsatile blood pump).
- **Dataset II:** in this case the computational cardiovascular simulator was used. The simulator was set in order to reproduce a large number of medical realistic cases defined and determined by specialists (see Fig. 6 for more details). In each of these cases the pump was activated and the speed was progressively increased till suction appeared. A total of 26 pump flow signals of approximately 20 h were produced, in different medical cases and with different predefined pathologies.

In the GMM model only one time varying parameter was selected, the mean of the non-suction mixture. Reducing the degrees of freedom in the model ensures higher reliability [31]. For learning the initially GMM parameters we build an initial dataset with the following steps:

- For the NS signal we calculate the average M.
- The average, M, is removed from the whole signal.
- A window processing is applied on the new signal, calculating the average over a 1-s window in the case of pump flow signals from the Dataset I and over a 0.1-s window in the case of pump flow signals from the Dataset II.



Cases	Pathologies										rpm_suction
	HC	IC	DC	RVF	ISF	AR	AS	AT	SH	PH	
1	0	2	2	0	0	0	0	0	2	0	26000
2	0	2	2	0	0	0	0	0	0	0	24000
3	0	2	2	0	0	1	0	0	0	0	24000
4	0	2	2	2	0	0	0	0	2	0	26000
5	0	2	2	0	0	3	0	0	0	0	22000
6	0	2	1	0	0	3	0	0	0	0	22000
7	0	3	1	2	1	0	0	0	0	0	24000
8	0	1	1	0	1	0	0	0	0	0	28000
9	0	1	1	0	0	0	1	0	0	0	28000
10	0	1	3	0	0	0	0	2	0	0	28000
11	2	0	0	0	1	0	2	0	1	0	26000
12	0	3	2	1	0	0	0	2	0	1	26000
13	3	0	0	0	1	2	0	0	0	0	26000
14	0	0	2	1	0	1	0	0	0	2	24000
15	0	0	2	3	0	0	0	0	0	0	20000
16	0	3	0	0	0	0	0	0	0	1	24000
17	0	0	1	3	0	0	0	0	0	0	22000
18	0	2	0	3	0	0	0	0	0	1	22000
19	0	0	2	3	0	0	0	0	0	1	20000
20	0	0	3	2	0	0	0	0	0	1	20000
21	0	3	0	2	0	0	0	0	0	0	22000
22	1	1	0	0	0	0	1	0	0	0	26000
23	0	0	3	0	0	0	0	0	0	3	20000
24	3	0	0	0	0	0	2	0	0	0	26000
25	0	1	2	0	0	0	0	0	0	0	26000
26	0	1	1	3	0	0	0	0	1	0	24000

Fig. 6. A screenshot of the VHSP along with realistic patients' pathologies for 26 different cases as they were defined by the specialists. Hypertrophic Cardiomyopathy: HC, Ischemic Cardiomiopathy: IC, Dilated Cardiomiopathy: DC, Right Ventricular Failure: RVF, Interventricualr Septum Failure: ISF, Aortic Regurgitation: AR, Aortic Stenosys: AS, Aterosclerosis: AT, Systemic Hypertension: SH, pulmonary hypertension: PH.

From the dataset obtained, the initial GMM parameters are estimated (Table 2) [30]. Segments of the signal with higher probability on the second mixture are considered as S (Fig. 7). The parameter *D* for the GMM model is initially estimated using the pump flow simulation dataset. For each signal, the 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 D. The estimation of D using the two datasets was -0.5. Then for each of the 36 signals in the two datasets the methodology was applied. The first five seconds of the signals were used for the estimation of an initial mean μ_B and the standard deviation σ_B. Then for each 1-s window (in the case of pump flow signals from Dataset I) and 0.1-s window (in the case of pump flow signals from Dataset II) the classification and adaptation steps were applied. In the classification based step each segment is categorized as NS or S based on the probabilities.

In order to quantify the performance of our methodology the ROC curves for the detection of suction in the 10 signals of the dataset I are given in Fig. 8(a). The area under curve (AUC) was 0.97. In addition, the ROC curve for the detection of suction in the 26 signals of the Dataset II is given in Fig. 8(b). The confusion matrices, sensitivities, specificities and the total accuracy are given in Tables 3 and 4 for the two datasets, respectively. Signal windows were classified as suction events when the GMM component corresponding to suction had probability larger than the 0.5; otherwise they were classified as no suction.

Table 2
GMM Parameter estimation.

Parameter	Value (VAD heart simulation platform)	Value (numerical simulator)
μ_B	-0.01	-0.01
D	-0.46	-12
σ_B	0.08	3.8
σ_S	0.25	6

4. Discussion

In this study, the SensorART SSM is described in detail. It is a novel set of tools assisting specialists in effectively assessing and exploiting simulated patient data, in order to design the best treatment strategy for their patients before and after LVAD implantation, analyze acquired datasets, extract new knowledge, and make informative decisions. The nature of the tools implies that a wide variety of specialists are expected to utilize this system, as indicated by our usability testing in three different user groups such as cardiac and vascular surgeons, cardiologists and general clinicians as well as biologists and researchers. Furthermore, the SensorART SSM will be potentially used to transfer the success and deductions of the most experienced cardiosurgery centers to those less established. In general, LVAD therapy entails processing complex, uncertain, and incomplete data, which are dynamically evolving. As a consequence, the centers with a larger patient volume are at an advantage compared with those that treat only a few LVAD patients per year. The introduction of the SensorART SSM will enable the potential to translate valuable

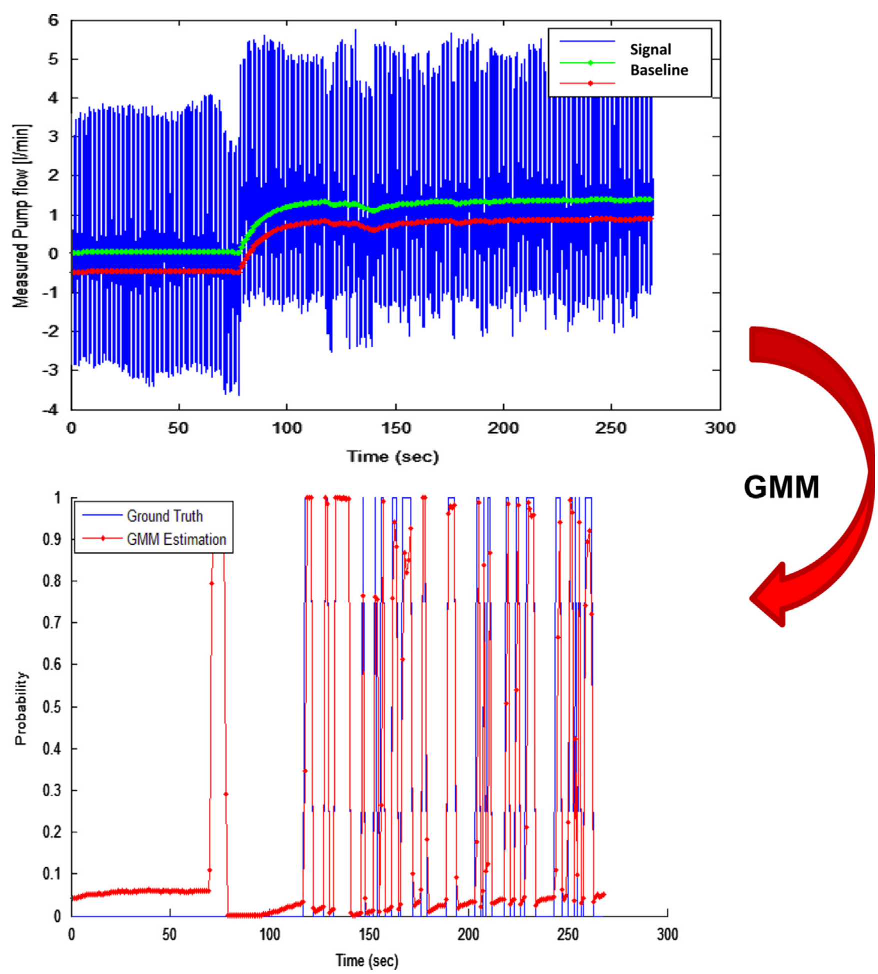


Fig. 7. Online GMM Parameter Estimation [31].

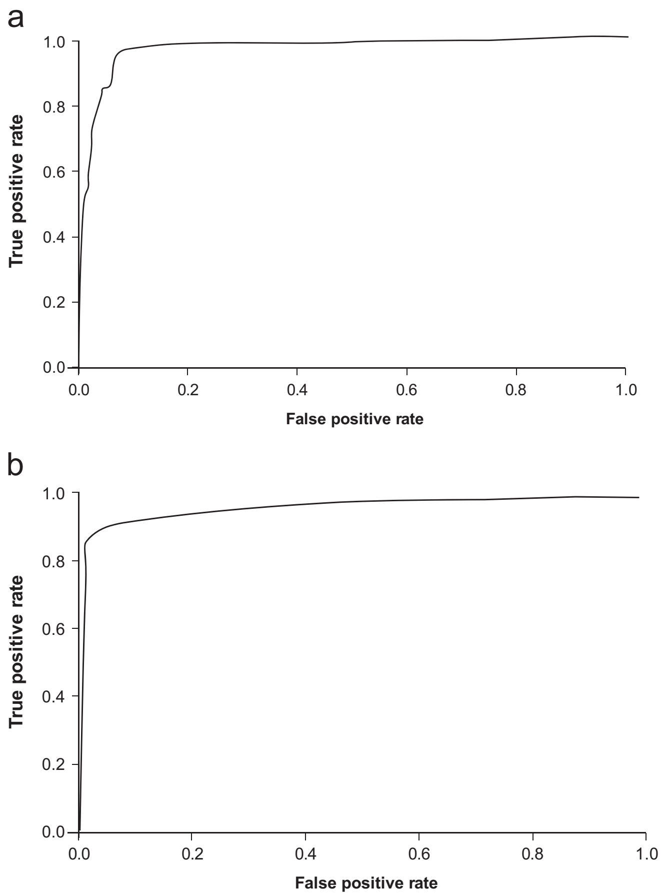


Fig. 8. (a) ROC curve for the GMM classification (AUC=0.97) for Dataset I. (b) ROC curve for the GMM classification (AUC=0.9657) for Dataset II.

Table 3
The above results are from 10 signals with approximately 46 min duration, where GMM online estimation was applied (Dataset I).

	GMM no suction	GMM suction
No-suction	1904	71
Suction	117	510
Sensitivity	96%	81%
Specificity	94%	88%
Accuracy		93%

Table 4
The results are from 26 signals with approximately 20 h duration, where GMM online estimation was applied (Dataset II).

	GMM no suction	GMM suction
No-suction	63,547	1568
Suction	3480	4555
Sensitivity	98%	57%
Specificity	95%	74%
Accuracy		**93%**

expert knowledge into standardized, personalized, and optimized LVAD therapy.

This study focused on the preliminarily evaluation of the SensorART SSM and especially the Suction Detection Tool through a set of representative simulation sessions. As the SensorART platform is mainly focused on Circulite pump, implanted in atrio-aortic connection, this study focus on suction detection in the left atrium. Certainly, the validation of the suction detection module is not complete and does not cover all the possibilities of suction in general, but the present study is a first attempt in evaluating the suction detection module in specific conditions. The literature presents various methods applied for suction detection in LVADs. As it is already mentioned, the majority of the related works addressed 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 the suction detection 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 in public. Although a direct comparison is not feasible, in Table 5, a comparison of the methods reported in the literature is presented. Additional processing of patient data in real life LVAD applications may be of crucial importance in suction detection and speed selection. Namely, during practical usage such as animal trials, sampled data may not be as clean as in the model simulations. The artefact in signals may produce similar thresholds as the ones that we defined in this study. This essentially increases the probability of false positives, events that trigger LVAD controller action to prevent suction when suction is not actually taking place. Thus, data integration (smoothing) and cubing may be a good method of improving robustness.

Future development of the SMM will include the option of predicting or anticipating the suction phenomenon from the change of the slope of the pump flow signal. This will also allow the development of a closed control algorithm for LVAD which incorporates physiological parameters as inputs. The changes in these parameters are strongly related to the physiological condition of the patient and his exercise intensity. By including this information as control input, the controller relates the pump speed to these changes and can improve the pump support for the patients with changing physiological state.

5. Conclusions

In this study, the SensorART Speed Selection Module is presented which mainly consists of two SDSS tools and the VHSP.

In general, the SDSS is a web-based application that offers specialists with a plethora of tools for monitoring patients, designing the best therapy plan, analyzing data, discovering new knowledge, making informative decisions and selecting the optimal pump speed. In this context, the SensorART SSM (Suction Detection and Speed Selection Tool) provides an important functionality that is directly related to the optimal use of the LVAD system (appropriate speed) and consequently the wellness of the patient. It allows specialists to safely evaluate different sets of parameters, identify the patient–device interactions, and determine suitable treatment strategies through virtual trial and error of specific pathologies. Future developments will include a closed-loop operation of a sensorized LVAD through a set of implantable/wearable sensors and a minute to minute assessment.

Conflict of interest statement

The authors declare that they have no competing interests.

Table 5
Suction detection methods presented in the literature.

Author(s)	Year	Suction detection methods		Pump or suction states	Results
		Feature extraction	**Classification**		
Ferreira et al. [22]	2006	**Time-domain analysis** • Zero-crossings **Frequency-domain analysis** • Harmonic index • Subharmonic index **Time-frequency analysis** • Instantaneous frequency	Thresholding function	I. NS II. SS	For SS detection Sensitivity:88% Specificity:95%
Ferreira et al. [23]	2006	**Time-domain analysis** • Asymmetry index • Max, Min Pump Flow envelopes • Max, Min dQ/dt envelopes **Frequency-domain analysis** • Harmonic index • Subharmonic index **Time-frequency analysis** • Instantaneous frequency	Discriminant analysis	I. NS II. MS III. SS	Total Accuracy: 73.8% NS Accuracy: 69.9% MS Accuracy: 84% SS Accuracy: 85.8%
Vollkron et al. [20]	2006	**Time-domain analysis** • Asymmetry criterion • Plateau criterion • Slow rate criterion • Low flow criterion • Mean-Min-Max criterion • Saddle-Neg criterion • Saddle-Pos criterion	Thresholding function	I. NS II. MS III. MPS IV. SS V. U	False positive rate:0.42% False negative rate: 1.5%
Karantonis et al. [21]	2007	7 Features from the pump speed signal	Classification and regression tree (CART)	I. NS II. SS	For SS detection Sensitivity: 99.11% Specificity: 98.76%
Karantonis et al. [28]	2008	9 Features from the pump speed signal	Artificial Neural Networks (ANN)	I. NS II. SS	For SS detection Sensitivity: 98.54% Specificity: 99.26%
Wang et al. [24]	2011	**Time-domain analysis** • Mean, minimum, and maximum values of the pump flow signal **Frequency-domain analysis** • Harmonic and subharnomic energy content of pump flow signal **Time-frequency analysis** • Standard deviation of Instantaneous Frequency	Lagrangian Support Vector Machines (LSVMs)	I. NS II. MS III. SS	Total Accuracy: 93.2% NS Accuracy: 92.9% MS Accuracy: 93.3% SS Accuracy: 94.6%
Wang et al.[30]	2013	**Time-domain analysis** • Mean, minimum, and maximum values of the pump flow signal **Frequency-domain analysis** • Harmonic and subharnomic energy content of pump flow signal **Time-frequency analysis** • Standard deviation of Instantaneous Frequency	Lagrangian Support Vector Machines (LSVMs)	**Dataset I:** (3-state) I. NS II. MS III. SS (2-state) I. NS II. SS **Dataset II:** (3-state) I. NS II. MS III. SS	**Dataset I:** For SS detection (3-state): Sensitivity: 98.6% Specificity: 99.6% Total Accuracy: 99.4% For SS detection (2-state): Sensitivity: 98.7% Specificity: 99.6% Total Accuracy: 99.4% **Dataset II:** For SS detection (3-state): Sensitivity: 95% Specificity: 99.1% Total Accuracy: 98.8% For SS detection (2-state): Sensitivity: 95% Specificity: 99.1% Total Accuracy: 98.8%

Table 5 (*continued*)

Author(s)	Year	Suction detection methods		Pump or suction states	Results
		Feature extraction	**Classification**		
				(2-state) I. NS II. SS	
The proposed Suction Detection Methodology [31]	2013	**Gaussian Mixture Model (GMM)** • Signal windowing • GMM based classification • GMM parameter adaptation	Gaussian Mixture Model (GMM)	I. NS II. SS	**Dataset I:** For SS detection: Sensitivity: 81% Specificity: 88% Total Accuracy: 93% **Dataset II:** For SS detection: Sensitivity: 57% Specificity: 74% Total Accuracy: 93%

No suction (NS), Moderate suction (MS), Most probably suction (MPS), Severe suction (SS), Not classified/posterior analysis (ND), Not useful (NU), Undecided (U).

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References

[1] K. Dickstein, A. Cohen-Solal, G. Filippatos, J.J. McMurray, P. Ponikowski, P.A. Poole-Wilson, A. Stromberg, D.J. van Veldhuisen, D. Atar, A.W. Hoes, A. Keren, A. Mebazaa, M. Nieminen, S.G. Priori, K. Swedberg, ESC guidelines for the diagnosis and treatment of acute and chronic heart failure 2008: the Task Force for the diagnosis and treatment of acute and chronic heart failure 2008 of the European Society of Cardiology. Developed in collaboration with the Heart Failure Association of the ESC (HFA) and endorsed by the European Society of Intensive Care Medicine (ESICM), Eur. J. Heart Fail. 10 (2008) 933–989.

[2] J.R. Boston, J.F. Antaki, M.A. Simaan, Hierarchical control of heart-assist devices, IEEE Robot. Autom. Mag. 10 (2003) 54–64.

[3] Antaki J.F., Choi S., Amin D.V., Boston J.R., Yu Y.C., Kerrigan J.P., Konishi H., Litwak P., Borovetz H.S., and Griffith B.P., In search of chronic speed control for rotary pumps, in: Proceedings of the Waseda International Congress of Modeling and Simulation Technology for Artificial Organs, Japan, 1996.

[4] Antaki J.F., Choi S., Boston J.R., Butler K.C., Thomas D.C., and Amin D.V., Speed control system for implanted blood pumps, US Patent 6,066,086: Nimbus Inc, 2000.

[5] H. Konishi, J.F. Antaki, D.V. Amin, J.R. Boston, J.P. Kerrigan, W.A. Mandarino, P. Litwak, K. Yamazaki, M. Macha, K.C. Butler, H.S. Borovetz, R.L. Kormos, Controller for an axial flow blood pump, Artif. Organs 20 (6) (1996) 618–620.

[6] T. Waters, P. Allaire, G. Tao, M. Adams, G. Bearnson, N. Wei, E. Hilton, M. Baloh, D. Olsen, P. Khanwilkar, Motor feedback physiological control for a continuous flow ventricular assist device, Artif. Organs 23 (6) (1999) 480–486.

[7] G.A. Giridharan, M. Skliar, Physiological control of blood pumps without implantable sensors, Proc. Am Control Conf. 1 (2003) 471–476.

[8] M. Oshikawa, K. Araki, K. Nakamura, H. Anai, T. Onitsuka, Detection of total assist and sucking points based on the pulsatility of a continuous flow artificial heart: in vivo evaluation, ASAIO J 44 (5) (1998) 704–707.

[9] G.A. Giridharan, M. Skliar, Nonlinear controller for ventricular assist devices, Artif. Organs 26 (11) (2002) 980–984.

[10] G.A. Giridharan, M. Skliar, D.B. Olsen, G.M. Pantalos, Modeling and control of a brushless DC axial flow ventricular assist device, ASAIO J. 48 (3) (2002) 272–289.

[11] S.M. Parnis, J.L. Conger, J.M. Fuqua Jr., R.K. Jarvik, R.W. Inman, D. Tamez, M.P. Macris, S. Moore, G. Jacobs, M.J. Sweeney, O.H. Frazier, Progress in the development of a transcutaneously powered axial flow blood pump ventricular assist system, ASAIO J 43 (5) (1997) 576–580.

[12] Chen S.H., Baroreflex-based physiological control of a left ventricular assist device (Thesis), The School of Engineering, University of Pittsburgh, 2006.

[13] McConahy D.C., Application of multiobjective optimization to determining an optimal left ventricular assist device (LVAD) pump speed. (Thesis), The School of Engineering, University of Pittsburgh, 2007.

[14] L. Fresiello, K. Zieliński, S. Jacobs, A. Di Molfetta, K.J. Pałko, F. Bernini, M. Martin, P. Claus, G. Ferrari, M.G. Trivella, K. Górczyńska, M. Darowski, B. Meyns, M. Kozarski, Reproduction of continuous flow left ventricular assist device experimental data by means of a hybrid cardiovascular model with baroreflex control, Artif. Organs (2013), http://dx.doi.org/10.1111/aor.12178 (Oct 1).

[15] A. Di Molfetta, S. Jacobs, L. Fresiello, T. Verbelen, M.G. Trivella, B. Meyns, G. Ferrari, Simulation of apical and atrio-aortic VAD in patients with transposition or congenitally corrected transposition of the great arteries, Int. J. Artif. Organs 1 (37) (2014) 58–70 (Jan 30), http://dx.doi.org/10.5301/ijao.5000264.

[16] G. Ferrari, M. Kozarski, K. Zielinski, L. Fresiello, A. Di Molfetta, K. Gorczynska, K. J. Palko, M. Darowski, A modular computational circulatory model applicable to VAD testing and training, J. Artif. Organs 15 (1) (2012) 32–43.

[17] M. Kozarski, G. Ferrari, K. Zieliński, K. Górczyńska, K.J. Pałko, L. Fresiello, A. Di Molfetta, M. Darowski, A hybrid (hydro-numerical) cardiovascular model application to investigate continuous-flow pump assistance effect, Biocybern. Biomed. Eng. 32 (4) (2012) 77–91.

[18] B. Meyns, A. Simon, S. Klotz, T. Wittwer, C. Schlensak, F. Rega, D. Burkhoff, Clinical benefits of partial circulatory support in New York Heart Association Class IIIb and Early Class IV patients, Eur. J. Cardio-thorac. Surg. 39 (2011) 693–698;
A. Di Molfetta, S. Jacobs, L. Fresiello, T. Verbelen, M.G. Trivella, B. Meyns, G. Ferrari, Simulation of apical and atrio-aortic VAD in patients with transposition or congenitally corrected transposition of the great arteries, Int. J. Artif. Organs 1 (37) (2014) 58–70 (Jan 30).

[19] M. Darowski, M. Kozarski, G. Ferrari, K. Zieliñski, K. Górczyñska, A. Szczepanowski, K.J. Palko, L. Fresiello, A. Di Molfetta, A new hybrid (hydro-numerical) model of the circulatory system, Bull. Pol. Acad. Sci. – Tech. Sci. 61 (4) (2013) 993–1003, http://dx.doi.org/10.2478/bpasts-2013-0107.

[20] M. Vollkron, H. Schima, L. Huber, R. Benkowski, G. Morello, G. Wieselthaler, Advanced suction detection system for an axial blood pumps, Artif. Organs 30 (9) (2006) 665–670.

[21] D.M. Karantonis, N.H. Lovell, P.J. Ayre, D.G. Mason, S.L. Cloherty, Identification and classification of physiologically significant pumping states in an implantable rotary blood pump, Artif. Organs 30 (9) (2006) 671–679.

[22] Ferreira A., A rule-based controller based on suction detection for rotary blood pumps (Thesis), The School of Engineering, University of Pittsburgh, 2007.

[23] Ferreira A., Chen S., Simaan M.A., Boston J.R., Antaki J.F., A discriminant analysis-based suction detection system for rotary blood pumps, in: Proc. IEEE EMBC, 2006 pp. 5382–5385.

[24] Wang Y., Faragallah G., Divo E., and Simaan M.A., Detection of Ventricular Suction in an Implantable Rotary Blood Pumps Using Support Vector Machines, in: Proc. 2011 IEEE Engineering in Medicine and Biology Conference, Boston, MA, August 30 – September 3, 2011, pp. 3318–3321.

[25] A. Yuhki, E. Nogawa, M. Miura, Y. Shimazaki, S. Takatani, Detection of suction and regurgitation of the implantable centrifugal pump based on the motor current waveform analysis and its application to optimization of pump flow, Artif. Organs 23 (6) (1999) 532–537.

[26] Liu D., Boston J.R., Lin H., Antaki J.F., Simaan M.A., Wu J., Monitoring the development of suction in an LVAD, in: Proc. BMES-EMBS 1st Joint Conf., 1999, pp. 240.

[27] M Oshikawa, K Araki, G. Endo, H. Anai, M. Sato, Sensor less controlling method for a continuous flow left ventricular assist device,, Artif. Organs 24 (8) (2000) 600–605.

[28] D.M. Karantonis, S.L. Cloherty, N.H. Lovell, D.G. Mason, R.F. Salamonsen, P.J. Ayre, Noninvasive detection of suction in animplantable rotary blood pump using neural networks,, Int. J. Comput. Intell. Appl. 7 (3) (2008) 237–247.

[29] Morello, Gino F., Blood pump system and method of operation, US Patent: 0215050, 2004.
[30] M.A. Yu Wang, Simaan, A suction detection system for rotary blood pumps based on the lagrangian support vector machine algorithm, IEEE J. Biomed. Health Inf. 17 (3) (2013) 654–663, http://dx.doi.org/10.1109/TITB.2012.2228877.
[31] Tzallas A.T., Rigas G., Karvounis E.C., Tsipouras M.G., Goletsis Y., Zielinski K., Fresiello L., Fotiadis D.I., and Trivella M.G., A Gaussian mixture model to detect suction events in rotary blood pumps, in: IEEE Twelfth International Conference on BioInformatics and BioEngineering-BIBE 2012.
[32] G. Rigas, Y. Goletsis, D.I. Fotiadis, Real-time driver's stress event detection,, Intell. Transp. Syst. IEEE Trans. 13 (1) (2012) 221–234.