A 4-Layer Supervising Unit for Extra-Corporal Circulation

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Abstract—Extra-corporal Circulation Support Systems (ECCS) are used in cardiac surgery on a daily basis. Surgeons and perfusionists supervise patients' vital signals such as heart rate or blood pressure and ensure secure and errorless operation of the ECCS. Latest developments clear the way to use an ECCS for emergency circulatory resuscitation in non–clinical environments, even when trained staff is sparse and when there is no standard monitoring setup. There is urgent need for computerized ECCS supervision.
In this work we highlight the requirements and specifications of a supervising unit (SU) that monitors patient and machine status during extra-corporal circulation. We describe a conceptual framework architecture based on a 4–layer design, that implements such a SU and furthermore introduce a template matching algorithm based on cross-correlation and the Hilbert transformation for real-time patient monitoring. We show how the algorithm integrates into the framework and illustrate that such autonomous supervising instances can help to increase system safety and quality of care.

Index Terms—Patient monitoring, template matching, signal processing

I. INTRODUCTION

In the last decades, heart-lung machines (HLM) became a routinely used device in cardiac surgery. Due to technological advances, they became smaller in size, lighter and more easy to use. A particular HLM, the Lifebridge B2T, was designed to be used in emergency situations and during transportation, e.g. in an ambulance. The plug–and–play characteristics of this device allow operation by trained staff, perfusionists and non–perfusionists alike. Clinical results of this portable and modular ECCS were recently presented [1]. Patients suffering from cardiogenic shock benefit from an early application of an ECCS, preventing multi–organ failure.

Even though the portability of this device opens up new possiblities, it implies some challenges. Trained personnel is sparse in emergency situations and space in ambulances is limited. There is no surgical team as in a regular operating theater, there is no standard system setup. Monitoring devices are not available, medical records of the patient are usually unknown and a comprehensive anamnesis is unfeasible. An adequate and secure operation of a HLM under such circumstances needs supervision.

A promising approach to effectively operate the HLM in non–clinical environments can be to automate the ECCS based on online data from the patient. An autonomous HLM ideally provides optimal perfusion while minimizing the workload of a human operator in stressful situations. Ongoing research deals with an automatic pump speed regulation of the Lifebridge HLM, considering its application in non-clinical environments. A prototype fuzzy controller that regulates the pump speed of the HLM was developed and preliminary results were already published [2]–[4]. Based on the patient's mean arterial pressure (MAP) and the produced pump flow, the controller decreases or increases the pump speed of the ECCS following a rulebase designed by cardiac surgeons.

Automatic perfusion control has been addressed in quite a few publications [5]–[7]. Also fuzzy control was applied to several medical questions [8]–[10]. It seems especially suited for automatic perfusion since it manages vague and ambigious data and easily maps expert knowledge into a technical system via simple IF–THEN rules. However, there has been no approach presented yet, that autonomously ensures patient and system safety during extra–corporal circulation. An automated ECCS possibly reduces the workload of a human operator, but it would still need human supervision, especially when used in emergencies or during transportation. Sensors might fail, cannulation tubings might get kinked, vibrations during transportation can influence system performance. These unpredictable, situational events heavily influence control behavior and thereby set the patient at imminent risk. To manage such risks and still ensure a robust control scheme elaborate algorithms for patient and system monitoring are needed. Automatic detection of life-threatening events or device-malfunction is indispensable in order to provide optimal perfusion. Such algorithms and security features further reduce the personnel's workload. In this work we present a framework for a SU that accounts for such problems. The requirements and goals of this framework are highlighted and we outline its architecture. Furthermore we present a template matching algorithm that detects characteristic patterns in a MAP signal and present preliminary results.

II. Methods

A. A Framework for Physiological Signal Analysis, Patient and Device Monitoring

In literature quite a few frameworks for medical data analysis can be found. Most of them are designed for specific applications and operate on databases of medical records. These tools can be used to define and follow evidence–based therapy guidelines and became well–known as Clinical Decision Support Systems (CDSS). Chiarugi et al. [11] highlight the advantage of such systems and integrate signal and image processing methods to treat heart failure. Garg et al. [12] give a systematic summary on the effects of CDSS on patient and practitioner performance. Recently Apiletti et al. [13] introduced a flexible framework for physiological signal processing which also includes data mining methods to assess a patient's health status and to detect potential risks.

The requirements and specifications for such systems are manifold and strongly depend on the application. The main objectives are to increase system safety, patient safety and thereby quality of care. In this work we introduce a concept for supervising automated ECCS. The tasks of our SU are to monitor patient and system status, to extract meaningful information from given data streams, to deduce the overall patient and system status as well as to notify an user on important changes, events or possible danger. Furthermore the SU shall influence the decision making of an ECCS controller. To cover these various tasks we propose a conceptual framework, based on a 4–layer architecture, depicted in Fig. 1.

1) Data Acquisition Layer: The bottom layer deals with data acquisition issues. It manages data recordings from sensors and retrieval from databases as well as basic preprocessing methods such as filtering or handling of missing values. In the specific case of the Lifebridge HLM and accompanying experiments, multiple data streams are recorded. These include crucial patient data such as blood pressure, blood flow, ECG and SPO$_2$ values as well as machine parameters like the pump speed, produced flow and in- and outlet pressures. A detailed description of the used sensors and data recording management can be found in [4]. Simple reasoning clarifies the importance of this layer: the quality of the recorded signals (e.g. Signal-to-Noise Ratio (SNR)) strongly effects the results of downstream analysis methods and performance of any follow-up layer.

2) Data Analysis Layer: The second layer encompasses signal processing methods for data analysis. The objective of this layer is to extract parameters relevant in the decision making from the given data streams. Standard features include the calculation of minimum, maximum and mean values of a signal. Especially in medical data analysis distance to given threshold values (alarm thresholds), long and short–term trend analysis is of interest (see [13]). Also pattern detection methods such as QRS detection for ECG signals or the algorithm described below belong to this layer.

3) Data Abstraction Layer: The data abstraction layer shifts extracted features onto a semantic level. Using data mining methods signal features and detected patterns are
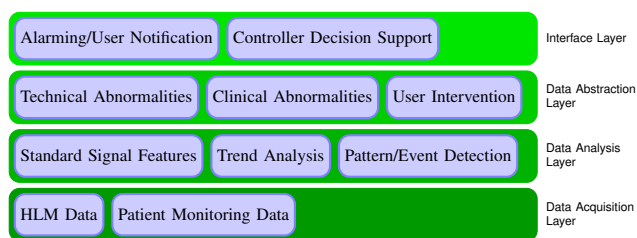

Fig. 1. Layout of supervising unit illustrating the required informational levels from sensoring to user interaction.

translated into relevant and exploitable information. This layer accounts for unimodal as well as multi–modal data mining. In most of the current literature, analysis and decision making is done in a unimodal manner, i.e. data is acquired and features are extracted without considering possible correlations in between separate channels. However, using possibly redundant information from several data channels can help to detect sensor failures and other risks. For example the heart rate can be extracted from both ECG signals and a pulse oximeter. Strong deviation of the two values would indicate some sensoring problem. Generally, the data abstraction layer extracts meta–information from the data streams. It scans for technical abnormalities (e.g. sensor failure), clinical risks (e.g. cardiac fibrillation) and user interventions, i.e. a SU should be aware if the user directly interacts with the system, e.g. manual control of the ECCS.

4) Interface Layer: The top layer of our SU interfaces with the user and the controller's decision making. As described before, a fuzzy controller is able to regulate the HLM's pump speed based on simple rules. Considering information about the overall system status and the patient's constitution improves adequate control. Inappropriate decisions caused by sensoring problems, situational events or user interventions can be reduced when integrating information from a SU. Linking meta–information between the SU and the fuzzy controller can for example be realized via extra input parameters that assess system and patient status in an index–like manner. An extended rulebase can then account for the additional knowledge. E.g. a simple rule can be not to change pump speed if only transient pressure changes were observed but the long–term signal trend stays constant. Apart from interfacing with the controller the SU should notify and warn an operator about imminent and life–threatening risks and events in a consistent way. This includes event logging for a post–operational analysis as well as intelligent information management to alarm the user in an ergonomic way, e.g. via a display.

5) Summary: A 4–layer architecture expresses an intuitive way for SU development. The object–oriented character of the framework allows implementation in high–level languages and clearly separates different tasks of the SU. This eases maintenance and allows later extensions. So far, we implemented the framework in C++ with focus on the data acquisition and analysis layer. We integrated standard analysis techniques as well as trend analysis as described in [13].

B. Template Matching for Patient Monitoring Systems

Apart from standard signal extraction methods, our framework allows to integrate more advanced algorithms as well. In this section we present a template matching algorithm for patient monitoring and use it to detect blood pressure curves recorded by a MAP sensor. The presented algorithm can be helpful to detect sensor failure and noise as well as general changes in the signal (increase, decrease, heart beat variations). Our matching is based on the normalized cross–correlation between a given template and a signal. Usually blood pressure peaks and the associated characteristic waveform occur roughly periodically in the signal. This results in a cosine–like cross-correlation coefficient when the template is continuously shifted over the signal. The template and the search signal are alternately in–phase and in counter–phase. However, we are only interested in the local maxima of the correlation coefficient, since they (and their connecting line) tell us the overall development of our matching. We exploit properties of the Hilbert transformation to calculate the upper envelope function of the correlation coefficient. This approach goes without separate calculation of local maxima and expensive interpolation methods.

1) Normalized Cross–Correlation: The cross–correlation is well–known for template matching, predominantly in the image processing domain. Generally spoken it measures the similarity between two signals x of size N and y of size M with $N < M$, expressed in the correlation coefficient. For 1D template matching, the search pattern is continuously shifted over a given signal and the correlation coefficient is calcuated for every time instance over the whole area spanned by the template. Given the time-discrete template $x[i]$ with $i = 1 \dots N$, we calculate the normalized cross–correlation coefficient with signal $y[k]$ for every sample point $k = 1 \dots M - N$:

$$r_{xy}[k] = \frac{\sum_{i=1}^{N}(x[i] - \bar{x})(y[i+k] - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x[i] - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y[i+k] - \bar{y})^2}}. \quad (1)$$

The denominator in equation 1 normalizes the correlation coefficient $r_{xy}[k]$ such that $-1 \leq r_{xy}[k] \leq 1$. Large values of $r_{xy}[k]$ indicate a good matching between the source signal and the template. Large negative values also indicate high correlation, but of the inverse of one of the time series, i.e. the signal and the template are inversely phased.

2) The Hilbert Transformation: Patterns in a physiological source signal, such as pressure or ECG curves are approximately periodic. Calculation of the normalized cross–correlation of such signals with a predefined pattern results in an amplitude and phase modulated cosine–like signal. These properties can be exploited to effectively calculate the upper envelope of $r_{xy}[k]$. Amplitude and phase modulated signals can generally be regarded as bandpass signals. In communications, the Hilbert transformation is often used to transfer a lowpass signal into a bandpass signal and vice versa, which is needed for signal modulation and demodulation. Given a real bandpass signal $x_{BP}(t)$, the so-called analytic signal $x_{BP}^{+}(t)$
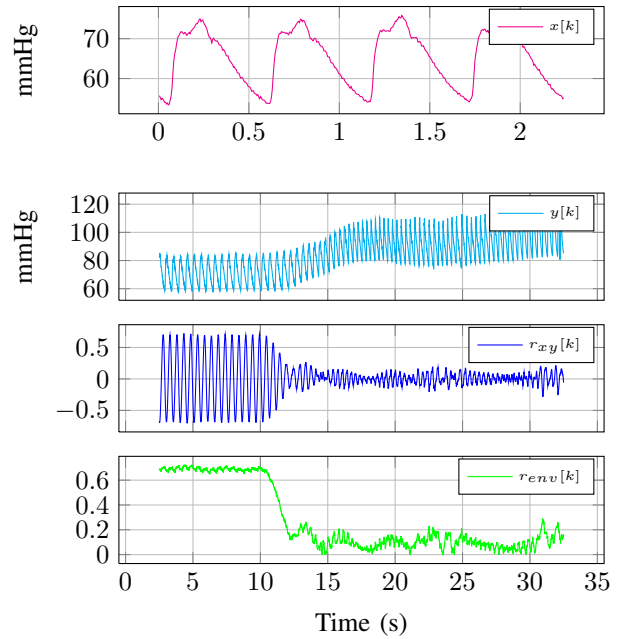

Fig. 2. From top to bottom the template $x[k]$, the search signal $y[k]$, their cross–correlation coefficient $r_{xy}[k]$ and its envelope function $r_{env}[k]$ are shown during drug administration. Both the search signal and the template were taken from an animal experiment.

reads

$$x_{BP}^{+}(t) = x_{BP}(t) + j\hat{x}_{BP}(t) \quad (2)$$

with the Hilbert transform $\hat{x}_{BP}(t)$. The analytic signal has no spectral components for frequencies smaller than zero. It can be shown, that the absolute value of the complex signal $x_{BP}^{+}(t)$ yields the envelope of the bandpass signal [14]. We use this knowledge to retrieve the envelope of $r_{xy}[k]$:

$$r_{env}[k] = \left\| r_{xy}^{+}[k] \right\| = \left\| r_{xy}[k] + j\hat{r}_{xy}[k] \right\|. \quad (3)$$

3) Experimental Setup and Results: The presented algorithm was integrated into the SU framework. During animal experiments with the Lifebridge HLM using ordinary pigs, multiple sensor data were recorded. These data can be analyzed and processed online or after the experiment, using the data records. To test our algorithm we used data from such an experiment. We randomly picked a template for a characteristic MAP curve that included 4 heart beats and that appear during a steady state extra–corporal circulation (see Fig. 2, 1st plot). As search signals, different patterns from the same experiment were chosen. They included ranges with no sensor data or noise, sharp and slow deviations from a steady state and sensor movement. Illustratively Fig. 2 shows an increasing MAP curve ($y[k]$) that was recorded during drug administration. Arterenol, a vasoconstrictor that increases the MAP, was administered. The plots below show the correlation coefficient $r_{xy}[k]$ as well as its envelope function $r_{env}[k]$. Starting from a steady state with a confidence level of about 70%, a drastic decrease in the matching result can be observed as soon as the pressure starts to increase, leading to a confidence level of 10% approximately.

Similar results (data not shown) were obtained in other test cases. An obvious drawback of this method, that is well-known for correlation–based template matching, concerns scaling issues. Since the blood pressure waveforms are not strictly periodic, the template never exactly matches any test signal. Considering $y[k]$ in Fig. 2 again, the matching confidence is only around 70% in the beginning, though this section of the signal is declared as a steady state. The matching confidence could be increased, if dynamic templates were used. If coupled with a heart beat detector, the template could be adjusted to an adequate time scale. This will be covered in future work. For now, we can state that the algorithm as presented here is fast, easy to implement and generally applicable to detect patterns in physiological data streams.

III. CONCLUSION

We presented a framework for an ECCS supervising unit, that allows the integration of different signal processing algorithms. The presented architecture consists of 4 layers that comprise different informational levels of monitored data. The SU monitors patient and system data and extracts relevant information from the data channels. In the data fusion layer this information is shifted onto a semantic level and can be used to influence automated perfusion control by interfering with a controller's decision making unit. Furthermore the SU warns an operator against imminent and life–threatening risks. Beyond that we introduced a template matching algorithm and illustrated its feasibility with detection of characteristic blood pressure curves. Our algorithm couples a correlation–based template matching with an effective strategy to calculate the upper envelope function of the correlation coefficient, which yields the overall matching result. Calculations of local maxima and spline – or other interpolation techniques are not needed. In preliminary experiments promising results were found. In future work, dynamic template matching will be covered. Template scaling, e.g. based on the current heart rate, would increase the matching confidence.

Generally, standard signal extraction methods and algorithms as described in this work help to detect deviations from a pre-defined state. They could be used to account for unpredictable situational events during extra–corporal circulation in non–clinical environments such a tube kinking or vibrations. By supervision, detection and classification of such events patient safety and quality of care can be increased.

REFERENCES

[1] M. Krane, D. Mazzitelli, U. Schreiber, A. Mendoza Garzia, B. Voss, C. Badiu, R. Lange, and R. Bauernschmitt, "First experience with a new portable cardiopulmonary bypass system - lifebridge b2t with percutaneous femoral cannulation," in *Computers in Cardiology*, 2008, pp. 269–272.

[2] B. Baumgartner, A. Mendoza, U. Schreiber, S. Eichhorn, M. Krane, R. Bauernschmitt, and A. Knoll, "A simple fuzzy controller for an extra-corporeal circulation system - limitations and potentials," in *5th Russian-Bavarian Conference on Bio-Medical Engineering*, 2009.

[3] U. Schreiber, S. Eichhorn, A. Mendoza, B. Baumgartner, R. Bauern-schmitt, R. Lange, A. Knoll, and M. Krane, "A new fuzzy controlled extracorporeal circulation system. first results of an in-vitro investiga-tion," in *Computers in Cardiology*, vol. 36, 2009.

[4] A. Mendoza García, B. Baumgartner, U. Schreiber, M. Krane, A. Knoll, and R. Bauernschmitt, "Automedic: Fuzzy control development platform for a mobile heart-lung machine," in *World Congress on Medical Physics and Biomedical Engineering*, ser. IFMBE Proceedings, vol. 25, 2009.

[5] F. Boschetti, S. Mantero, F. Miglietta, M. L. Costantino, F. Montevecchi, and R. Fumero, "An approach to computer automation of the extracor-poreal circulation," *Computers in Biology and Medicine*, vol. 32, no. 2, pp. 73–83, Mar. 2002.

[6] B. Misgeld, J. Werner, and M. Hexamer, "Robust and self-tuning blood flow control during extracorporeal circulation in the presence of system parameter uncertainties," *Medical and Biological Engineering and Computing*, vol. 43, no. 5, pp. 589–598, Oct. 2005.

[7] G. Meyrowitz, "Automatisierung der herz-lungen-maschine," Ph.D. dis-sertation, Universität Karlsruhe, 2005.

[8] D. A. Linkens, J. S. Shieh, and J. E. Peacock, "Hierarchical fuzzy modelling for monitoring depth of anaesthesia," *Fuzzy Sets and Systems*, vol. 79, no. 1, pp. 43–57, Apr. 1996.

[9] R. Bauernschmitt, J. Hoerer, E. Schirmbeck, H. Keil, G. Schrott, A. Knoll, and R. Lange, "Fuzzy-logic based automatic control of hemodynamics," *Computers in Cardiology*, vol. 30, pp. 773–776, 2003.

[10] D. Mason, J. Ross, N. Edwards, D. Linkens, and C. Reilly, "Self-learning fuzzy control of atracurium-induced neuromuscular block dur-ing surgery," *Medical and Biological Engineering and Computing*, vol. 35, no. 5, pp. 498–503, Sep. 1997.

[11] F. Chiarugi, S. Colantonio, D. Emmanouilidou, D. Moroni, and O. Sal-vetti, *Advances in Mass Data Analysis of Images and Signals in Medicine, Biotechnology, Chemistry and Food Industry*, ser. Lecture Notes in Computer Science. Springer, 2008, vol. 5108/2008, ch. Biomedical Signal and Image Processing for Decision Support in Heart Failure, pp. 38–51.

[12] A. X. Garg, N. K. J. Adhikari, H. McDonald, M. P. Rosas-Arellano, P. J. Devereaux, J. Beyene, J. Sam, and R. B. Haynes, "Effects of com-puterized clinical decision support systems on practitioner performance and patient outcomes: A systematic review," *JAMA*, vol. 293, no. 10, pp. 1223–1238, Mar. 2005.

[13] D. Apiletti, E. Baralis, G. Bruno, and T. Cerquitelli, "Real-time analysis of physiological data to support medical applications," *Information Technology in Biomedicine, IEEE Transactions on*, vol. 13, no. 3, pp. 313–321, 2009.

[14] A. Mertins, *Signal Analysis. Wavelets, Filter Banks, Time-Frequency Transforms and Applications*. John Wiley & Sons, 1996.