Nour Aldeen Jalal*, Tamer Abdulbaki Alshirbaji, Bernhard Laufer, Paul D. Docherty, Thomas Neumuth and Knut Moeller

Changes of Physiological parameters of the patient during laparoscopic gynaecology

Abstract: Analysing and fusing data from the medical devices of different disciplines (anaesthesiology and surgery) inside the operating rooms may promote awareness during surgical procedures. In this work, the changes of physiological parameters of patients undergoing laparoscopic gynaecology procedures were analysed. The statistical relationship between the intra-abdominal pressure and airway peak pressure was evaluated. Patients ventilated with pressure-controlled ventilation (PCV) and intermittent mandatory ventilation (IMV) were included. The results demonstrated that increasing the intra-abdominal pressure (IAP) resulted in increasing the airway peak pressure and decreasing the lung compliance. The Pearson correlation coefficient between the IAP and the airway peak pressure was 0.910 in PCV-patients and 0.952 in IMV-patients when changes of the ventilation settings were considered. Additionally, major hemodynamic changes included alterations in the mean blood pressure (MBP), where the MBP increased after insufflating the abdomen and decreased after abdomen deflation.

Keywords: Laparoscopic procedure, Surgical actions, Context-aware systems, Lung mechanics.

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***Corresponding author: Nour Aldeen Jalal:** Institute of Technical Medicine (ITeM), Furtwangen University, Villingen-Schwenningen, Germany; and Innovation Center Computer Assisted Surgery (ICCAS), University of Leipzig, Leipzig, Germany, e-mail: ja@js-furtwangen.de

Tamer Abdulbaki Alshirbaji: Institute of Technical Medicine (ITeM), Furtwangen University, Villingen-Schwenningen, Germany; and Innovation Center Computer Assisted Surgery (ICCAS), University of Leipzig, Leipzig, Germany

Paul D. Docherty: Department of Mechanical Engineering, University of Canterbury, Christchurch, New Zealand; and Institute of Technical Medicine (ITeM), Furtwangen University, Villingen-Schwenningen, Germany

Thomas Neumuth: Innovation Center Computer Assisted Surgery (ICCAS), University of Leipzig, Leipzig, Germany

Bernhard Laufer, Knut Moeller: Institute of Technical Medicine (ITeM), Furtwangen University, Villingen-Schwenningen, Germany

1 Introduction

Operating theatres are continually improved by advances in medical devices and cutting-edge technologies [1-3]. However, a persistent need has arisen for smart systems, known as context-aware systems (CASs), to overcome the increasing complexity of the surgical workflow. The advances in machine learning and deep learning techniques with the growing ability to access much more surgical data have enabled researcher to introduce innovative ways to establish CASs in practice [3].

Indeed, many concepts and approaches have been introduced to describe and realise the components of CASs. For instance, recognising surgical activities [4-8], detecting surgical tools [6, 9-11] and predicting surgery duration [12] using various types of surgical data have been studied. Additionally, physiological data have been analysed to develop medical support models that predict patient state. Lundberg et al. proposed a machine learning approach for predicting the risk of hypoxaemia in patients under general anaesthesia [13]. However, studies that fuse surgical data and physiological data (data from different perspectives) are still lacking.

In this paper, datasets that contained synchronous real-time recordings from a patient monitor, anaesthesia machine and surgical devices of four patients undergoing gynaecological procedures were collected and analysed. The data were screened to ensure completeness and correctness. The changes in the blood pressure, lung mechanics and intra-abdominal pressure during the surgical procedure were evaluated.

2 Methods

2.1 Patients and Data

Data from four female patients who underwent laparoscopic gynaecology procedure were used. The data were recorded in

Table 1: Ventilation settings and target intra-abdominal pressure (IAP) for the included subjects. IMV is the abbreviation of intermittent mandatory ventilation, the PCV is the abbreviation of pressure-controlled ventilation, T is Trendelenburg, and L is Lithotomy.

Subject	Ventilation settings						Patient position	Target IAP [mmHg]
	Ventilation mode	Inspiration tidal volume (V_{Ti}) [mL]	Respiration frequency [1/min]	Inspiration/Expiration ratio (I:E ratio)	PEEP levels [mbar]	Ventilation pressure ($P_{insp.}$) [mbar]		
1	IMV	440 470	12 10 12 10 12	0.667 0.714	7	-	L	14
2	IMV	400 380	10 9 10 12 14 11	0.714	5 6 5	-	T	14
3	IMV	500 480	12 11 10 13 9	0.667 0.520	5	-	L	13
4	PCV		12 16 14 16 18 16	0.667 0.5	10 12 8 12 10 12 10	10 12 8 12 10 12 15 10	L + T	14

October and November 2020 at the Schwarzwald-Baar clinic in Villingen-Schwenningen, Germany. The data included real-time recordings from patient monitor, anaesthesia machine and surgical devices. A detailed description of the data recording system is provided in Abdulbaki Alshirbaji et al. [14]. The average time of the surgical procedures was 106 minutes. Three patients were ventilated with intermittent mandatory ventilation (IMV), a volume-controlled ventilation mode. One patient was ventilated via pressure-controlled ventilation (PCV). Detailed information about ventilation settings, patient position during the surgery, and target IAP are listed in Table 1.

The data recording system allowed synchronous recording of data streams from medical devices of different manufactures. However, raw data were pre-evaluated in terms of completeness and correctness. All data streams were cropped to the same start and end. Additionally, the clock skews of some devices introduced offset errors to the time stamps generated. Thus, the errors were corrected.

2.2 Data analysis

2.2.1 Signal filtering

To ensure consistency between the IAP signal and the airway pressure signal, the IAP signal was filtered using a low-pass FIR filter. The filter design was executed using the DSP system toolbox in MATLAB. The filter was designed for a sampling frequency of 25 Hz (the sampling rate of the IAP signal), with a passband frequency of 40 mHz and a stopband frequency of 100 mHz. The stopband attenuation and the

passband were set to 50 dB and 0.5 dB, respectively. The designed filter introduced a delay to the filtered signal. Therefore, the delay was estimated, and the filtered signal was shifted in time to line up the data.

2.2.2 Ventilation settings

The ventilation settings were sent by the anaesthesia machine every 60 seconds. Therefore, to get real-time values of the ventilation settings, monitored values were first identified from real-time waves (i.e. airway pressure, flow and volume). Then, the values were normalised according to the data received. In IMV-ventilated patients, the inspirational tidal volume was identified, and in the PCV-ventilated patient the maximum pressure was estimated.

2.2.3 Statistical analysis

The relationship between the IAP and the airway peak pressure was studied similarly to Jalal et al. [15]. The Pearson correlation coefficient (r) was calculated within each subject to establish the strength of the correlation between those two pressures. To normalise the influences of altering ventilation settings, multiple linear regression correlation between P_{peak} , IAP and ventilation settings was further analysed.

For the PCV-ventilated patients, the airway peak pressure had a linear trend component (see Figure 3). Thus, the trend component was subtracted from the signal prior to the analysis of the correlation. Figure 3 shows the peak airway pressure of subject 4, the trend component and the detrended peak pressure signal.

Figure 1: IAP, airway pressure and flow of two subjects. (a) IMV-ventilated patient (S1), (b) PCV-ventilated patient (S4). Filtered IAP is in red.

3 Results

The Pearson coefficient values for the correlations evaluated for each subject are presented in Table 2. The IAP, airway pressure and flow for Subject 1 (that is IMV-ventilated) and Subject 4 (that is PCV-ventilated) are shown in Figure 1. This shows the different characteristic changes to the flow curve between IMV- and PCV-ventilated patients. Figure 2 shows mean blood pressure (MBP) values at four different time points for all subjects.

Figure 2: Mean Blood Pressure at four time points. T1 and T2: 10 min before and after insufflation, respectively. T3 and T4: 10 min before and after abdomen deflation, respectively.

Figure 3: Original P_{peak} , trend component and detrended P_{peak} , exemplarily shown based on subject four.

Table 2: Pearson correlation coefficient for all subjects.

Subject	Pearson Coefficient (r)	
	P_{peak} with IAP	Multiple correlation
S1	0.946	0.962
S2	0.857	0.978
S3	0.736	0.917
S4	0.841	0.910
Mean $\pm$ std	0.845 ± 0.086	0.942 ± 0.033

4 Discussion & Conclusion

Experimental results obtained by this study illustrate the high correlation between the IAP and airway peak pressure (see Table 2). In accordance with previous studies [16, 17], increasing the IAP during laparoscopic procedures led to increase the airway peak pressure. The changes in ventilation settings had to be normalised to get the exact correlation between the IAP and P_{peak} . In the PCV-ventilated patient, the correlation was also high ($r = 0.910$). Changes in airway pressure caused by IAP can also be seen on both peak inspiratory and peak expiratory flow in PCV patients, but only on peak inspiratory flow in IMV patient (see Figure 1).

One of the main limitations of the present study is the limited number of subjects. Additionally, the medical history of the patients (e.g. lung injuries) should be considered in future work. Therefore, future work will incorporate more subjects and extend the concept of studying the relations between surgical actions and changes in patient state.

In conclusion, this study analysed the relationship between the IAP and the physiological parameters of the patients during laparoscopic procedures. Statistical relations obtained in this work form the basis for the development of pre-emptive medical support models.

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