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Effects of Intra-Abdominal Pressure on Lung Mechanics during Laparoscopic Gynaecology*

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Abstract— **Investigating the relations between surgical actions and physiological reactions of the patient is essential for developing pre-emptive model-based systems. In this study, the effects of insufflating abdominal cavity with CO_2 in laparoscopic gynaecology on the respiration system were analysed. Real-time recordings of anaesthesiology and surgical data of five subjects were acquired and processed, and the correlation between lung mechanics and the intra-abdominal pressure was evaluated. Alterations of ventilation settings undertaken by the anaesthesiologist were also considered. Experimental results demonstrated the high correlation with a mean Pearson coefficient of 0.931.**

Clinical Relevance— **This study demonstrates the effects of intra-abdominal pressure during laparoscopy on lung mechanics and enables developing predictive models to promote a greater awareness in operating rooms.**

I. Introduction

The analysis and modelling of medical data available in the operating room (OR) to increase informative knowledge have gained rising prominence over last years. Advances in machine learning techniques and increasing accessibility to medical data have encouraged an active research toward establishing decision support systems and pre-emptive approaches to optimise surgical treatment and patient outcomes [1, 2]. Ongoing advances aim to develop intelligent context-aware systems (CASs) that provide a greater awareness and a better collaboration between healthcare professionals from different medical disciplines, like anaesthesiology and surgery [1].

Efforts have been expended to analyse surgical data, such as laparoscopic videos, and employ machine learning for recognising surgical activities [3-6], classifying surgical tools [5, 7-9], detecting smoke [10] and predicting the remaining duration of the surgery [11, 12]. Furthermore, several approaches have made use of physiological data from anaesthesia machines and patient monitors, such as blood oxygen saturation (SpO_2), during surgery to develop analytical predictive models [13, 14]. For instance, Lundberg et al. introduced an approach that predicts the risk of hypoxaemia during general anaesthesia using pre- and intra-operative data [14]. However, approaches that fuse data from all available data yielding medical devices and probes are currently lacking. This is partly due to the lack of standardisation of data yielded by medical devices from different manufacturers in current clinical settings, and complexity of producing novel information from synthesising the data streams.

In fact, providing comprehensive explanations of physiological reactions of the patient to the surgical actions executed by the surgeon enables development of models for medical decision support. The use of these models enhances awareness of the anaesthesiologist and the surgeon, bridges the gap between them, and leverages, therefore, potential conflicts due to sometimes contradicting targets. In laparoscopy, the abdominal cavity is insufflated by carbon dioxide (CO_2) to create an operating field for the surgeon. Hence, the effects of the increasing intra-abdominal pressure (IAP) on respiratory system represent an important aspect that has been widely investigated [15-17].

In this study, real-time data from the anaesthesia machine, patient monitor and surgical devices (including insufflator, laparoscopic camera and electrosurgical unite) were synchronously recorded. The correlation between lung mechanics (i.e. airway peak pressure and dynamic lung compliance) and the IAP was evaluated. Moreover, changes in ventilation setting were also considered, and multiple correlations between the airway peak pressure, ventilation settings (i.e. respiratory frequency, inspiration tidal volume, inspiration expiration ratio (I:E ratio), positive end-expiratory pressure (PEEP)) and the IAP were determined.

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TABLE I. CHANGES OF VENTILATION SETTINGS AND THE TARGET INTRA-ABDOMINAL PRESSURE DURING THE SURGERY FOR THE INCLUDED SUBJECTS

Subject	Ventilation settings					Target IAP [mmHg]
	Ventilation mode	Inspiration tidal volume (V_{Ti}) [ml]	Respiration frequency [1/min]	Inspiration/ Expiration ratio (I:E ratio)	PEEP levels [mbar]	
1	IMV	440 | 470	12 | 10 | 12 | 10 | 12	0.667 | 0.714	7	14
2	IMV	400 | 380	10 | 9 | 10 | 12 |14 |11	0.714	5 | 6 | 5	14
3	IMV	500 | 480	12 | 11 | 10 | 13 | 9	0.667 | 0.520	5	13
4	IMV	500	12 | 10 | 12 | 14 | 10	0.588 | 0.769 | 0.909	5	15
5	IMV	450	14 | 16	0.667	12	14

II. METHODOLOGY

A. Measurements

Real-time data streams from patient monitor, anaesthesia machine and the surgical devices (e.g. insufflator) were acquired during laparoscopic gynaecology procedures. Data acquisition was executed in the integrated operating room (KARL STORZ OR1 FUSION) at the Schwarzwald-Baar clinic in Villingen-Schwenningen, Germany. A comprehensive explanation for the recording system and its specifications is provided in Abdulbaki Alshirbaji et al. [18]. Five procedures were included in this study. The procedures had a median length of 106 minutes (min 58, max 129).

B. Data processing

The raw data were initially processed in several steps to check for any incorrect recordings or missed samples. Data streams from different devices were then cropped to the same start and end. The start and the end of the procedure were chosen when the patient was connected and disconnected to the anaesthesia machine, respectively. Finally, errors in the clock skews received from the involved devices were identified and corrected.

The airway peak pressure, Positive end-expiratory pressure (PEEP) and tidal volume were identified from the real-time data. The dynamic lung compliance was also calculated according to the following equation:

$$C_{dyn} = \frac{V_T}{P_{peak} - PEEP} \quad (1)$$

Where C_{dyn} is the dynamic lung compliance, V_T is the tidal volume, P_{peak} is the airway peak pressure.

The IAP signal was filtered using a low-pass Finite impulse response (FIR) filter prior to compute the correlation. The low-pass filter had a stopband frequency of 100 mHz and a passband frequency of 40 mHz, where the sampling frequency of the IAP signal was 25 Hz. The original and filtered signals for the first subject are visualised in Figure 1.

C. Statistical analysis

The airway peak pressure and the static dynamic compliance were linearly correlated with the IAP. The Pearson correlation coefficients (r) were calculated within each subject. Moreover, further analysis taking into consideration the effect of the changes in the ventilation settings during the surgical procedure was proposed (details to the changes in ventilation settings during the procedure for all subjects are listed in Table I). Therefore, multiple correlations between the airway peak pressure and both the IAP and the changes in ventilation settings were evaluated as following:

- The correlation between airway peak pressure and the IAP and respiration frequency (termed multiple correlation 1).
- The correlation between airway peak pressure and the IAP and ventilation settings represented by respiration frequency, inspiration/expiration ration (I:E ratio), Inspiration tidal volume and PEEP (termed multiple correlation 2).

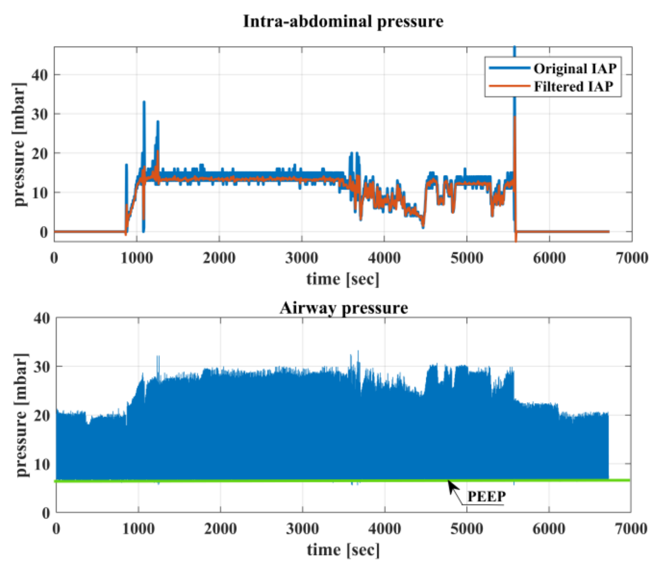

Figure 1: Real-time recordings of the intra-abdominal pressure and airway pressure for the first subject. Original and filtered IAP are shown in the top figure.

III. RESULTS

The correlations between the airway peak pressure (P_{peak}), the dynamic lung compliance (C_{dyn}) and the IAP for the second and fourth subjects are exemplarily illustrated in Figure 2. Additionally, the multiple correlations between the airway

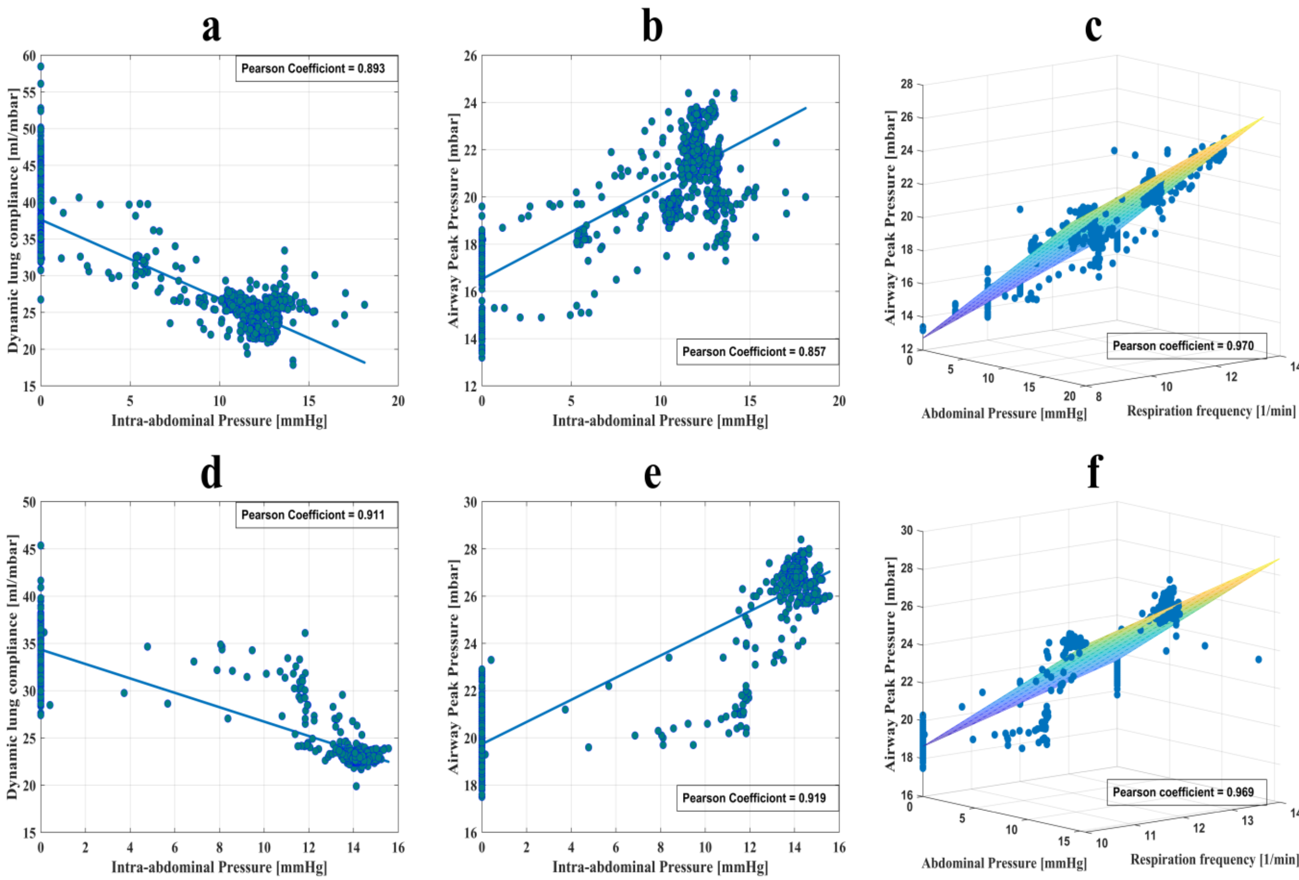

Figure 2: Correlation between intra-abdominal pressure and lung mechanics for two subjects (top and bottom, respectively). a and d show the correlation between the IAP and the dynamic lung compliance, while b and e show the correlation between the IAP and the airway peak pressure. c and f show the multiple correlation between the airway peak pressure and both the IAP and the respiration frequency. Pearson coefficients are presented on each figure.

peak pressure and the respiration frequency and the IAP are also shown in Figure 2. Table II presents the evaluated Pearson coefficients for the studied correlations. Pressure-volume curves of the respiratory system at two different IAP levels (i.e. before the insufflation and after the insufflation) are presented in Figure 3.

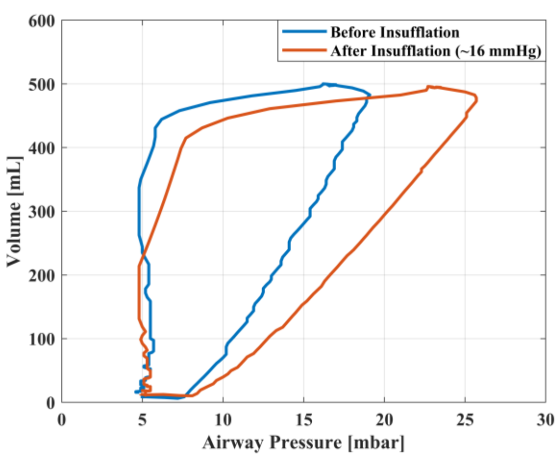

Figure 3: PV-curve obtained before insufflating the abdominal cavity with CO_2 and after insufflation. The loop is shifted to the right since the airway pressure increases when the abdominal pressure is increased.

TABLE II. PEARSON CORRELATION COEFFICIENTS FOR INCLUDED SUBJECTS.

Subject	Pearson correlation coefficient (r)		
	P_{peak} with IAP	Multiple correlation 1	Multiple correlation 2
1	0.946	0.955	0.962
2	0.857	0.970	0.978
3	0.736	0.754	0.917
4	0.919	0.969	0.989
5	0.80	0.812	0.812
Mean ± std	0.852 ± 0.085	0.892 ± 0.102	0.932 ± 0.072

IV. DISCUSSION

The main findings of this study explain that the application of intra-abdominal pressure during laparoscopy resulted in changes of the airway peak pressure. Furthermore, this study in accordance with previous studies [15-17] demonstrated that when the IAP increases the airway peak pressure increases and the lung compliance decreases (see Figure 2). Correlation coefficients (Pearson coefficient r) of 0.946 and 0.919 for subject 1 and subject 4 showed that the airway peak pressure is highly correlated to the changes of IAP. But the r values for the subjects 2, 3 and 5 were lower.

The changes in the settings of ventilation also affect the airway peak pressure. The ventilation mode used for all subjects was the Intermittent mandatory ventilation (IMV) that is a volume-controlled mode. Hence, increasing the respiration frequency, increasing the PEEP, decreasing the I:E ratio or increasing the tidal volume causes a rising airway peak pressure. Therefore, to get the exact correlation between the airway peak pressure and the IAP, changes caused by altering ventilation settings have to be normalised. In this context, models that incorporate changes in the aforementioned ventilation settings were further analysed.

Pearson correlation coefficients for all subjects were improved when the respiration frequency through the surgical procedure was considered (see Table II). The respiration frequency for subject 1 was either 12 or 10, while it was changed across five different values for subject 2 (see Table I). Therefore, the Pearson coefficient was better improved for subject 2 when the multiple correlation between the airway peak pressure, the IAP and the respiration frequency was analysed (see Table II). Additionally, the Pearson correlation coefficients for almost all subjects (except subject 5) were improved when all ventilation settings were involved in the correlation analysis.

Characteristic changes to the pressure-volume (PV) curve were also observed after insufflating the abdominal cavity (see Figure 3). The PV-loops were plotted at the same PEEP and tidal volume before and after the insufflation. The curve was extended to the right and the slope of the inspiration phase decreased. These changes occurred because of a change in compliance due to the IAP increase which affects the airway peak pressure that is reached when the same tidal volume is delivered.

This study has limitations. A limited number of subjects was included, and neither the medical history (e.g. lung injuries) nor the anatomical characteristics such as BMI of the subjects were considered. Therefore, further studies should include higher number of patients, and classify the patients into different groups based on their medical history and demographics. Furthermore, some other factors that may affect respiratory system mechanics have to be considered such as, the positioning of the patient and the neuromuscular blockade.

V. Conclusion

In this study, the correlation between lung mechanics and intra-abdominal pressure was analysed. Statistical relations obtained in this work set the stage for developing predictive models that improve situational awareness in the OR. Future work will incorporate the effects of insufflating abdomen with CO_2 on the cardiovascular system. Moreover, the concept of correlation between surgical actions and body reactions will be further extended, and the effects of additional surgical actions such as tissue cutting and coagulating will be investigated.

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