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Computer-assisted generation of anaesthesia report during laparoscopic procedures

https://doi.org/10.1515/cdbme-2023-1116

Abstract: Automatic generation of intraoperative anaesthesia reports has great potential to generate accurate and efficient documentation and allow the anaesthesiologists to utilise their time more optimally. However, automatically generating anaesthesia reports represents a demanding component in future operating rooms. In this paper, a computer-assisted system for anaesthesiology report generation during laparoscopic surgery is proposed. Data from anaesthesia machine, patient monitor, and surgical devices were acquired and analysed. The system proved to generate more accurate, efficient, and better readable reports compared to hand-written ones by clinicians. Moreover, additional information that describes surgical activities and events was also added by analysing surgical data.

Keywords: Anaesthesia Protocol, Data Fusion, Operating Room, Context-aware System, Medical Report.

1 Introduction

With an increasing focus on improving the treatment of patients, supporting surgical and anaesthesiologic teams, and enabling cost-effective usage of resources inside the surgical department, an innovation in data-driven, digitalised, and intelligent future operating rooms (OR) has been triggered [1]. Therefore, future OR will increasingly utilise intelligent systems that can process and analyse data streams of multiple perspectives, monitor the surgical treatment, conceive the surgical workflow, and provide the medical teams inside and outside the operating theatre with contextual knowledge [1].

Recent developments in data analysis and machine learning (ML), specifically deep learning (DL), have sparked active research on developing the intelligent components of the future OR [2]. In this context, approaches for the automatic analysis of the surgical workflow [3–6], recognition of surgical activities [4, 7–9], and the detection of surgical tools [5, 7, 9–12] have been introduced. Additionally, ML-based techniques have been proposed for the prediction of intraoperative events related to patient status. For instance, a logistic regression model was applied by Hatib et al. to predict hypotension using the arterial pressure signal. In our recent work [13, 14], a data fusion approach of anaesthesiological and surgical data was evaluated. The results emphasised the importance of combining multi-perspective data (i.e., from anaesthesiology and surgery) for the development of personalised medical support decision systems.

A potentially valuable application of the intelligent systems inside the OR is the automatic generation of surgical reports such as the anaesthesia report. In particular, Zamper et al. evaluated the reliability of computerised generation of anaesthesia reports during surgeries [15]. Their results showed great potential of using computerised reports to help anaesthesiologists and enhance data reliability. Moreover, the advantages of computer-assisted preoperative report generation in terms of accuracy, efficiency, and nurses' workload have been addressed [16]. However, the use of data-driven, automatic systems for anaesthesia report generation remains in development.

The data fusion approach presented in our previous work [13] provided a platform for automatic generation of intraoperative anaesthesia reports. The system relied on acquiring data from surgical devices, anaesthesia machine and patient monitor. Information that describes the vital signs of the patient and the settings of the anaesthesia machine through the surgical procedure was documented at adjustable regular intervals automatically from the data streams. Additionally, the system enables the anaesthesiologist to manually enter some information such as the airway management method and the size of the airway tube. Moreover, additional information that describes the surgical procedure (e.g., current surgical phase) was added by analysing surgical data such as the laparoscopic video.

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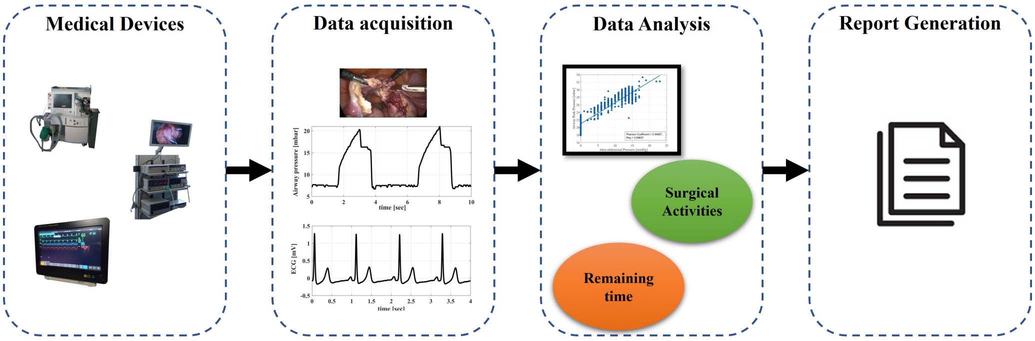

Fig. 1: Flow chart of the proposed system for the automatic generation of anaesthesia protocol. The medical devices include the anaesthesia machine, the patient monitor, and laparoscopic surgical devices. The data acquired includes device settings, alarms, and real-time waves (e.g., airway pressure, ECG, and temperature.)

2 Methods

The proposed system for computer-assisted generation of anaesthesia reports relies on acquiring data from the medical devices inside the OR, analysing and fusing data from multi-perspectives, and finally generating a report (see Figure 1).

2.1 Data Acquisition & Analysis

Data streams from the surgical devices, anaesthesia machine and patient monitor were recorded during laparoscopic procedures. The data collected is composed of device status information, device settings, actual values of surgical data, patient's vital parameters and ventilation settings. The data streams provided by various medical devices were synchronised using timestamps provided by the devices themselves. However, deviations in the device-related timestamps were observed and corrected. Additionally, data was pre-processed and checked in terms of correct and complete recording to ensure consistency between data streams. Detailed information about the recorded data can be found in [13].

By analysing surgical (e.g., laparoscopic videos and surgical device data) and physiological data using deep learning and machine learning techniques (e.g., convolutional neural networks (CNN)), contextual information about the current status of the surgical procedure can be extracted and added to the anaesthesia report. For instance, the start and end of abdomen insufflation, bleeding, and main surgical events.

2.2 Report Generation

The proposed system documents the vital signs of the patient (systolic and diastolic blood pressure, heart rate, airway pressure, positive end-expiratory pressure (PEEP), respiratory minute volume, respiration frequency) at regular intervals (5 minutes). Additionally, the system writes the ventilation settings such as ventilation mode. Moreover, the system allows manual input of information, such as intubation type and the size of the airway tube.

3 Results

Table 1 shows the full components of the generated anaesthesiology report. Figure 2 shows a qualitative comparison between a hand-written anaesthesiology protocol and an automatically generated protocol. The information presented in both reports includes settings of the anaesthesia machine (such as ventilation mode) and the vital signs of the patient, namely systolic and diastolic blood pressures, heart rate, respiration frequency, respiratory minute volume, airway peak pressure and PEEP.

4 Discussion & Conclusion

The integration of computer-assisted systems into the OR for the automatic generation of anaesthesia reports facilitates accurate documentation and easy recovery of information compared to conventional hand-written reports. As can be seen from Figure 2, the hand-written report had no clear handwriting, while the automatically generated report is clear and legible. This will allow more simple retrieval of surgical information. Moreover, the computerised report is more consistent and contains accurate information. For instance, the ventilation mode was documented as only pressure-controlled ventilation (PCV) by the anaesthesiologist/nurse anaesthetist during the entire procedure, while the synchronised pressure-controlled ventilation (S-PCV) and the spontaneous modes were also implemented (see Figure 2-(1)).

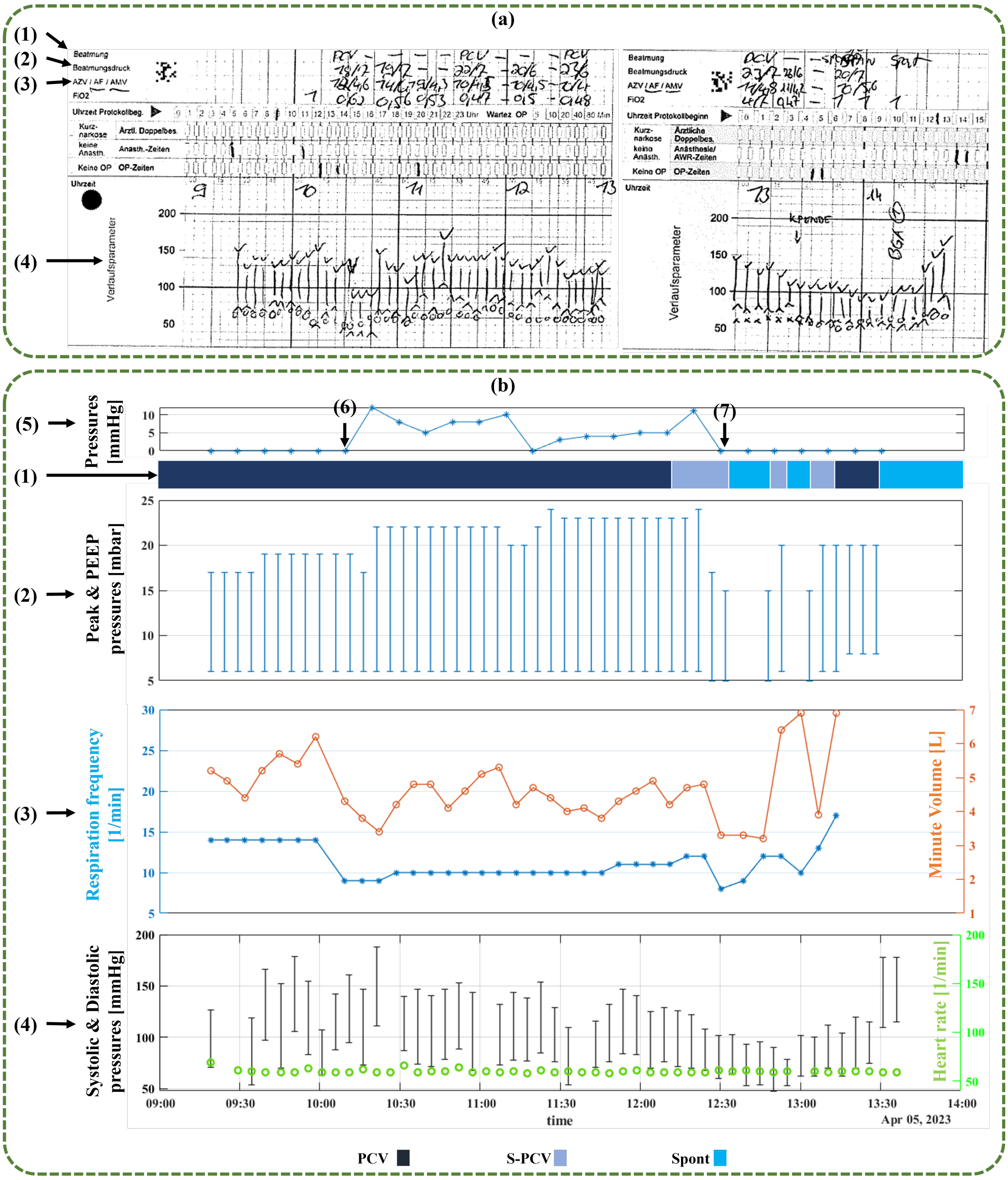

Fig. 2: An example of hand-written anaesthesia protocol (a) and automatically generated protocol (b). (1) The ventilation mode during the entire procedure, (2) the peak and PEEP pressures, (3) The respiration frequency and the minute volume, (4) The systolic and diastolic pressures, and the heart rate, (5) intra-abdominal pressure, (6) and (7) start and end of abdomen insufflation, respectively. PCV is the pressure-controlled ventilation mode, S-PCV is the synchronised pressure-controlled ventilation mode, and Spont is the spontaneous breathing mode.

Furthermore, adopting computer-assisted documentation of anaesthesia protocol promises relief to the anaesthesiologic team. However, it is critical that the report is manually checked. It is also worth mentioning that additional information was also added by analysing surgical data (see Figure 2-(6) & (7)).

The main limitation of this study is the lack of clinical evaluation. Therefore, the applicability of the proposed system prototype will be evaluated and validated in future work. Additionally, the lack of data interoperability standards between medical devices of different manufacturers represents a key challenge for integrating this prototype into all hospitals.

Tab. 1: Main information and patient parameters documented in the anaesthesia report. TV, RF, and MV are tidal volume, respiration frequency, and minute volume, respectively.

Type of Information	Method
Beginning of the surgery	automatic
End of the surgery	automatic
Beginning of the anaesthesia	automatic
End of the anaesthesia	automatic
Drug/Dose	manual
Fluids	manual
Type of anaesthesia	manual
Anaesthesia method	manual
Airway management	manual
Size of airway tube	manual
Positioning	manual/automatic
Vital signs	automatic
(Temperature, blood pressure, ECG)	
Ventilation mode	automatic
Peak airway pressure/ PEEP	automatic
TV / RF / MV	automatic
FiO2	automatic
etCO2	automatic

Author Statement

Research funding: This work was supported by the German Federal Ministry of Research and Education (BMBF) under grant CoHMed/DigiMedOP grant no. 13FH5I05IA. Conflict of interest: Authors state no conflict of interest. Informed consent: Informed consent has been obtained from all individuals included in this study by the anaesthesiologist. Ethical approval: The study complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the ethics commission of the Furtwangen University (application Nr. 19 -0306LEKHFU).

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