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Automatic Detection of Endotracheal Intubation During the Anesthesia Procedure

This paper is concerned with the mathematical modeling and detection of endotracheal (ET) intubation in children under general anesthesia during surgery. In major pediatric surgeries, the airway is often secured with an endotracheal tube (ETT) followed by initiation of mechanical ventilation. Clinicians utilize auscultation of breath sounds and capnography to verify correct ETT placement. However, anesthesia providers often delay timely charting of ET intubation. This latency in event documentation results in decreased efficacy of clinical decision support systems. In order to target this problem, we collected real inpatient data and designed an algorithm to accurately detect the intubation time within the clinically valid range; the results show that we are able to achieve high accuracy in more than 96% of the cases. Automatic detection of ET intubation time would thus enhance better real-time data capture to support future improvement in clinical decision support systems. [DOI: 10.1115/1.4033864]

1 Introduction

Mechanical ventilation is commonly used in emergency rooms, intensive care units, and operating rooms when there is a clinical need to assist or replace spontaneous breathing of the patient. In general, a mechanical ventilator is a machine that generates and regulates the flow of air to the patient's respiratory system. Using the mechanical ventilator, the clinician can control the flow of the air to the patient's airway by setting the different modes of ventilation.

Neonates, infants, and children undergoing major and complex surgeries in the U.S. undergo anesthesia and hence are mechanically ventilated for the period of the surgery. As a part of mechanical ventilation and to secure the airway during surgery, the anesthesiologist performs ET intubation, defined as the placement of an ETT in the trachea. Optimally, the ETT must be placed 0.2–2 cm from the carina depending on the child's size and weight [1,2].

In general, the enhancement and closed-loop control of mechanical ventilation has been the subject of some research studies during the past few decades [3–6]; however, modeling of ET intubation, which is one of the fundamental parts of mechanical ventilation, has not been carried out.

Endotracheal intubation is an especially complex problem in neonates and younger children due to the very small size of their trachea. Neonates and infants have short airways, and accurate

positioning of the ETT is crucial for adequate mechanical ventilation [7]. Intubation is one of the most important aspects of any surgery since securing the airway is needed to ensure adequate oxygenation of the patient. Failing to do so would cause a drop in oxygen saturation, which, if not treated urgently, would result in the patient's death. Oxygen saturation measurements are often made at the patient's fingertip, but this is usually a delayed indicator of poor oxygenation. Such a delay could be very hazardous in neonates and children since their oxygen reserve is very small. Unfortunately, malpositioning of the ETT and failure to insert the ETT into the trachea are very common in operating rooms and intensive care units. In fact, studies have shown that junior clinicians such as residents and fellows [8,9] fail to perform intubation correctly in more than 50% of the cases [2,10]. Another study by Sanders et al. [11] showed that the success rates for intubation are 37–51% for residents, 70–89% for fellows, and 72–94% for attending physicians. This statistic is particularly important since residents are often in charge of intubation. Furthermore, head and neck movements can induce inadvertent ETT movement. This movement can result in inadvertent extubation and endobronchial intubation especially in neonates and infants [12], which in turn will cause desaturation and consequently, patient death.

Rapid confirmation of correct ETT placement is clinically crucial because tube malposition is associated with serious adverse outcomes [2,13]. In an effort to address this problem, various techniques have been applied to enable correct tube placement and optimal positioning of ETT in the trachea. These techniques include: (a) chest radiography [14], (b) clinical examination (auscultation and bilateral chest rise) [15,16], (c) measurement of tube length using body parameters [17], (d) fiber optic techniques [18], (e) respiratory function monitors, (f) capnography, and (g)

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ultrasonography [19]. There are also various devices which have been proposed for detection and identification of the ETT position [7].

Of all these approaches, the gold standard for ETT tube position detection is chest radiography, which unfortunately has a time delay as the patient needs to be prepared for radiography; it is also of course associated with cost as well as unnecessary radiation exposure to the child. The auscultation of equal and bilateral breath sounds suggests that the ETT is above the carina. However, auscultation as a sole method cannot rule out endobronchial intubation [19,20]. The measurement of tube length in adults is a reliable method of ETT position detection but in neonates and infants it is not very dependable due to the small trachea size. There are several formulae that have been proposed to achieve correct tube placement [17,21]. These formulae have a linear correlation with gestational age but have a nonlinear correlation with weight. Furthermore, these rules do not apply to nasotracheal intubation [20,21]. The fiber optic technique is very helpful for tube placement but needs a specialized equipment, needs a physician adequately trained in this technique, and is associated with a time delay for the equipment setup [22]. A respiratory function monitor can measure airway gas pressure and flow and also the tidal volume (TV). However, neither gas flow nor airway pressure monitoring can distinguish tube placement in the trachea from one of the main bronchi. The ultrasonography technique needs personnel trained in this technique and specialized equipment, thereby making it a costly and time-consuming technique [2].

There have been many studies on ET intubation. For instance, there are many studies that focus on airway management, correlation between postsurgery complications and difficult airways [23,24], detecting intubation through the use of imaging or auscultation techniques [25], and control of mechanical ventilation [26–29]. To the best of our knowledge, there is no published study on automatic detection of the intubation time in patients (children or adult). There is, however, an urgent clinical need for a decision support system to automatically detect ETT position in the lung and trachea. The desired algorithm would ideally use the data that are already collected by the anesthesia machine, such as respiratory rate (RR), TV, peak inspiratory pressure (PIP), and end-tidal carbon dioxide (EtCO₂) to detect the tube position with high accuracy. Note that EtCO₂ is defined as the partial pressure or maximum concentration of CO₂ at the end of exhalation process, for which the normal values are 35–40 mm Hg.

We can divide the problem of tube misplacement detection into two steps [13,30]. These are: (i) detection of tube placement in the trachea (ET intubation) and (ii) discrimination of one lung from two lung ventilation. In this paper, we aim to address the first part of this problem and will explore the development of an algorithm based on the data that are collected from the anesthesia machine.

2 Methods

This section presents our approach for the design of the algorithm based on the available data to detect ET intubation in children. In the remainder of this section, we describe the mechanical ventilation in more detail and also discuss how the modes of the mechanical ventilation can affect the data and hence our algorithm design.

2.1 Modes of Mechanical Ventilation. In general, the mode of the mechanical ventilation describes the primary method of inspiratory assistance by the machine. Specifically, we can control either the volume of air (TV) or the pressure of air (PIP) generated by the machine. The clinician will determine a preset volume or pressure, and then, the machine generates a flow of gas into the lungs until, respectively, the predetermined volume or pressure has been delivered. Mechanical breaths or RRs may be controlled (meaning that the ventilator is active and the patient is passive), or be assisted (meaning that the patient initiates the breath and may or may not participate in the breath).

Table 1 Effect of mode on the mechanical ventilation variables during intubation

Mode	RR	TV	PIP	EtCO ₂
VC	Fixed	Fixed	↑	↑
PC	Fixed	Var	Fixed	↑
VS	Var	Var	↓	↑
PS	Var	Var	↑	↑
VAF	Fixed	Fixed	↑	↑

VC is volume control, PC is pressure control, VS is volume support, PS is pressure support, and VAF is volume auto flow. ↑ indicates increase in the variable during the intubation, while ↓ indicates decrease in the value.

The main impact of the mode of mechanical ventilation on our analysis is its effect on the mechanical ventilation related variables. The morphology of most of the ventilation variables, such as RR, PIP, positive end-expiratory pressure, and TV, depends heavily on the ventilator mode and settings. For instance, breathing could be spontaneous or under ventilator control. Moreover, controlled forms of ventilation could deliver either a preset PIP or TV. Table 1 shows the relationship between the mode of mechanical ventilation, mechanical ventilation variables, and intubation. This table shows how different ventilation variables are affected by the mode of ventilation during anesthesia and especially intubation. Table 1 reveals an interesting fact: unlike other mechanical ventilation variables, the changes in the EtCO₂ pattern remain the same regardless of the mode of ventilation. As a result, we will use EtCO₂ as the main variable to develop the algorithm. In the sequel, we will investigate changes in its pattern due to intubation.

2.2 EtCO₂ Pattern During the Intubation. Next, we discuss the induced changes in the EtCO₂ volume as a function of different events that continue to happen during anesthesia and particularly during the intubation procedure. In general, during anesthesia with mechanical ventilation, the anesthesiologist starts with mask ventilation. Mechanical ventilation recordings from the mask generally have a high variation due to the fact that mask sealing is usually not perfect leading to gas leakage, which causes noisy and unreliable recordings. Next, in some surgeries, the intravenous line is placed to allow for the possibility of injecting more anesthetics (if needed) to get the patient to the desired level of anesthesia. Then, usually, a fresh gas flow is turned off immediately prior to tube placement. This will cause a sharp drop in the values of the recordings. Note, however, at this step, we will still not have zero recordings due to the existence of residual gas in the ventilation circuit. In the next step, the ETT will be inserted in the trachea, and then, it will be connected to the ventilation circuit. Next, one of the anesthesia team members will hand-ventilate the patient to confirm chest rise and capnography (EtCO₂) recordings. At this point, we will see a spike in EtCO₂ and pressure recordings due to the high influx of air. After confirmation of the tube placement, the anesthesiologist will assess the tube depth for catching any tube misplacement that may occur. After assessment of leakage and possible cuff inflation, the attending physician may disconnect the tube from the circuit to tape it for better stability. At this point, the patient is ready for surgery. After tube placement, we may still observe variation in the recordings as a result of possible leakage in the circuit. However, the magnitudes of these variations are usually smaller than the variations seen in the mask ventilation phase.

Figure 1 shows an example of real data collected at the Children's Hospital of Philadelphia during Tonsillectomy and Adenoidectomy (T&A) surgery on an 8-year-old male child. The bottom part of the figure shows the magnified section from the beginning until approximately 10 mins after the intubation. This figure exemplifies the complexity of the task of detecting the intubation time. As explained earlier, there are so many steps that happen during the anesthesia as part of preparing the patient for surgery,

Fig. 1 Top: An example of actual EtCO₂ data collected during a T&A surgery. Bottom: A sample of events during intubation. 1, turning off fresh gas flow; 2, intubation; 3, hand ventilation; and 4, taping.

which affect the parametric data that are collected from the anesthesia machine in different ways. We should also note that not all of these steps happen during all the types of surgeries and even all the cases of one type of surgery. For example, taping of the tube after putting it in mainly just occurs in T&A surgery.

2.3 Algorithm Design. In this section, we discuss the steps involved in the algorithm design for detecting ET intubation. Based on our earlier discussion, we can summarize the main changes in EtCO₂ during anesthesia as follows: (i) before the intubation, recording have smaller magnitudes and are noisier and (ii) after intubation, recording magnitudes are higher and are less noisy. In mathematical terms, mask ventilation recordings (before intubation) have low mean, high frequency, and high variance, while the ETT recordings have higher mean, low frequency, and small variance. Three features are defined to detect the intubation time based on these observations from the trends in the data. We calculate these features for a moving window of the signal. The extracted features from the data are: (i) mean, (ii) variance, and (iii) the wavelet coefficient's variation index.

The biomedical signals are often nonstationary, i.e., their frequency content varies over time, since the patient's state of health typically changes dynamically. This can also be inferred from Fig. 1 as we can observe the changes in frequency, mean, etc., of the EtCO₂ signal over time. Wavelet transform is generally considered to be the optimal way to analyze nonstationary signals.

The continuous wavelet transform possesses the ability to construct a time–frequency representation of a signal that offers very good time and frequency localization as shown by the previous studies [31–33]. Hence, we used continuous wavelet transforms (CWT) to analyze the nonstationary behavior of the EtCO₂ signal in this paper.

As is well known, the CWT of a signal $x(t)$ is defined by Eq. (1), and given here for completeness

$$C(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

where a is the time scale, b is the transitional value, and ψ^* is the complex conjugate of the mother wavelet function ψ ; however, there is no standard method to choose a mother wavelet function for a specific problem. In this study, we used the Morlet function (defined by Eq. (2)) as a mother wavelet function; it may be noted that this is often the function of choice in the literature for nonstationary signals

$$\Psi_k(t) = C_k \pi^{-0.25} e^{-0.5t^2} (e^{ikt} - e^{-0.5k^2}) \quad (2)$$

where k allows for a tradeoff between time and frequency resolutions. We define the variation index of wavelet coefficients as

$$C_v = \frac{\sigma^2}{\mu^2} \quad (3)$$

where σ and μ are the standard deviation and mean values of the CWT coefficients, respectively.

As mentioned earlier, we calculate the features for a moving window of the signal and then analyze the trends of these features before and after the ET intubation. The results of the analysis are listed below:

- (1) *Mean of the windowed signal*: low during the mask ventilation, jumps during the intubation, and high after intubation.
- (2) *Variance of the windowed signal*: increases during the mask ventilation, reaches the maximum during the intubation, and decreases after intubation.
- (3) *Variation index of wavelet coefficients*: increases during the mask ventilation, reaches the maximum during the intubation, and decreases after intubation.

Based on these results, the intubation is flagged when each of these criteria is reached. The high level description of the designed algorithm is presented below:

High level description of the designed algorithm

1. EtCO₂ data are streaming
2. Start the window from N th recording
3. Calculate the following three features for window length L
 - (a) Mean
 - (b) Variance
 - (c) Variation index of wavelet features
4. Flag intubation time for each feature based on the analysis
5. Find the intubation based on the three flagged times

To find the exact intubation time based on the three flagged intubation times, we use the TV and PIP. We calculate the mean of TV and PIP before and after each of these three times. The time that correlates with the highest jump in the mean for these variables is flagged as the intubation time. This addition to the algorithm ensures its robustness as it provides another layer of checking for the intubation time. Figure 2 represents the schematic design of the developed algorithm. A sliding window with length L moves through the start to the N th recording of EtCO₂. At each increment, the three features, namely, mean, variance, and variation index, of wavelet coefficients are calculated from the data. Based on each of these features, a time instant is flagged

Fig. 2 Schematic overview of the designed algorithm

as the intubation time. The exact intubation time is then detected based on the information from the PIP and TV data. N and L are the design parameters of the algorithm, which are chosen and tuned based on the collected data.

Next, we describe the algorithm in mathematical terms.

High level description of the designed algorithm

1. $i = 1, j = 1, k = 1, C_{vi}^0 = 0, \Delta C_{vi} = 0, \Delta C_m = 0, \Delta C_v = 0$
2. initialize N & M & V
3. $P = N, M = N, V = N$
4. while $\Delta C_{vi} > \varepsilon_1$ (starts with wavelet variation index)
 - (a) calculate CWT coefficients at scale 50 (x),
 - (b) $s = (x(1), x(2), \dots, x(N))$
 - (c) calculate ΔC_{vi}^i
 - (d) calculate $\Delta C_{vi} = C_{vi}^i - C_{vi}^{i-1}$
 - (e) $P = P + 1, i = i + 1$
5. end while
6. while $\Delta C_m > \varepsilon_2$
 - (a) calculate mean of the window (m_j)
 - (b) calculate $\Delta C_m = m_j - m_{j-1}$
 - (c) $M = M + 1, j = j + 1$
7. end while
8. while $\Delta C_v > \varepsilon_3$
 - (a) calculate variance of the window (v_k)
 - (b) calculate $\Delta C_v = v_k - v_{k-1}$
 - (c) $V = V + 1, k = k + 1$
9. end while
10. return P, M , and V
11. $p_P = \text{mean}(\text{pip}(1 : P)), p_M = \text{mean}(\text{pip}(1 : M)), p_V = \text{mean}(\text{pip}(1 : V))$
12. $tv_P = \text{mean}(\text{tv}(1 : P)), tv_M = \text{mean}(\text{tv}(1 : M)), tv_V = \text{mean}(\text{tv}(1 : V))$
13. $p_{P+1} = \text{pip}(P + 1), p_{M+1} = \text{pip}(M + 1), p_{V+1} = \text{pip}(V + 1)$
14. $tv_{P+1} = \text{tv}(P + 1), tv_{M+1} = \text{tv}(M + 1), tv_{V+1} = \text{tv}(V + 1)$

Table 2 Design parameters of the algorithm

Parameter s	Values	Accuracy (%)
L	20	90
	25	90
	30	96
	35	91
	40	91
ε_1	0.045	92
	0.05	96
	0.055	93
ε_2	4.5	90
	5	96
	5.5	92
ε_3	0.9	89
	1	96
	1.1	92

15. $\Delta p_P = p_{P+1} - p_P, \Delta p_M = p_{M+1} - p_M, \Delta p_V = p_{V+1} - p_V$
16. Intubation time = index max ($\Delta p_P, \Delta p_M, \Delta p_V$)

3 Results and Discussion

To evaluate the performance of the designed algorithm, we have used patient data collected from inpatient operating rooms at CHOP over the last 4 years. The collected dataset consists of 600

Fig. 3 Example time series plot of the three features for a sample case

Fig. 4 Example cases for different cases. The vertical lines represent the flagged intubation based on the three measures.

de-identified patients varying in age between 1 and 18 years. The dataset consists of the relevant anesthesia machine variables (EtCO₂, PIP, and TV) with a sampling rate of 15 s. Additionally, the data consists of demographics of the patients, such as gender, type of surgery, weight, and patient position during the surgery. We would like to point out that this is parametric data which are

collected at a relatively low sampling rate; however, studies have shown that parametric data can be successfully used in the field of healthcare diagnostics. For instance, del Pozo et al. [34] and Her-mida et al. [35] mathematically proved that the minimum sampling rate required to develop a parametric representation of a blood pressure signal is 12 samples per day. Other studies,

Fig. 5 Examples of two subjects whose algorithm either (a) incorrectly detects the intubation time or (b) fails to detect the intubation

Fig. 6 Histogram plot of the time difference between actual intubation time and flagged intubation time determined by the algorithm

Table 3 Breakdown of the detection accuracy of each of the three features

Features	Accuracy (%)
Mean	79
Variance	72
Variation index	85

including ours, have also shown the successful implementation of parametric data in a variety of problems [36–39].

For a variety of reasons, such as disconnection of anesthesia machine, the patient data often contain wrong or missing measurements. The algorithm replaces the missing data with the last known data for the corresponding period. Additionally, the design parameters of the algorithm we used are listed in Table 2. This table shows the design parameters and accuracy of the algorithm based on the changes in these parameters. From this table, it is clear that the algorithm is most sensitive to the choice of ε_3 with 7% variation in the accuracy of the algorithm on changing this parameter. Based on the sensitivity analysis in this table, we have

used the following values for the parameters: $L = 30$, $\varepsilon_1 = 0.05$, $\varepsilon_2 = 5$, and $\varepsilon_3 = 1$.

Choice of N takes into account the fact that most of the cases begin with artifacts caused by a variety of reasons as the clinical team would be preparing the room or the patient and going through many other preparatory procedures. Our collected data showed that it usually takes 10 mins from start of the data collection until ET intubation. As a result, we choose N to be half of this, i.e., 5 mins or 20 samples. With this strategy, we were able to control the robustness of the algorithm. Figure 3 shows plots of mean, variance, and variation index for a sample case. In this particular case, all the features agree and point to the same spot as the intubation time.

Figure 4 shows the results on intubation detection time in some sample cases. The plots show the intubation time flagged by all the features and the exact intubation time based on TV or PIP data (the so-called ground truth). As plots show, in many cases, the flagged time by different features actually overlap with each other. In these cases, the algorithm is always capable of detecting the intubation time precisely.

It should be recalled that we have data from 600 patients. Our results show that the algorithm could precisely detect intubation time in 547 of those cases. In 32 cases, it could detect intubation time within three samples of the actual time which is still clinically reliable. The algorithm failed to converge and did not flag intubation in only four cases. In other words, the results show that the algorithm is capable of exactly detecting intubation in 91% of cases, and it can correctly detect intubation time within 1 min in 96% of cases.

Figure 5 represents two samples of algorithm misdetection. In the top figure, the algorithm detects the intubation 5 mins earlier than its actual time and in the bottom figure, it fails to detect the intubation time completely. These plots represent the patterns which lead to misdetection in the algorithm. By investigating the cases when the difference between actual and the detected intubation times is more than 1 min, we realized that the recordings are heavily affected by noise in all those cases. In four cases that the algorithm failed to converge, either the ET length was too short or the EtCO_2 was very low (less than 30 mm Hg). Our investigations showed that age or type of surgery has no effect on the algorithm's accuracy.

Figure 6 shows a histogram of the difference between actual intubation time and the detected intubation time. The red vertical lines represent the range for a clinically valid detection. Table 3 represents the number of times that each of the features exactly

detected the intubation time. This is an interesting table as it shows that the variation index is the best feature in detecting intubation. Interestingly, the mean is the second best feature and variance is the third best feature. This table shows that the wavelet transform is efficient in analyzing the nonstationary nature of the EtCO₂ signal. Furthermore, the mean value has a high correlation with the intubation time.

4 Conclusion

In this work, we addressed the important problem of automatic detection of ET intubation. We developed an algorithm based on the anesthesia machine variables, principally, EtCO₂, TV, and PIP. The algorithm uses EtCO₂ to flag candidate intubation times, following which we use TV or PIP to detect exact intubation time. We found that EtCO₂ is the most reliable variable for detecting intubation in mechanical ventilation since its morphology is not affected by the mode of ventilation. We extracted three features from the data in order to capture the trend of EtCO₂ during intubation. Based on each of these features, we flag an intubation time. To detect the exact intubation time, we use TV or PIP based on the mode of mechanical ventilation. The results of testing the algorithm on real data collected from inpatient operating rooms demonstrate the excellent performance of the algorithm. Application of the wavelet transforms makes the algorithm robust to noise inherent in the data collection. Additionally, validation of the results of EtCO₂ data with TV and PIP ensures the consistency of the algorithm and makes it independent of the mechanical ventilation mode. The results of the algorithm are naturally limited by the sampling rate of the data collection. Better sampling rate can be expected to improve the performance of the algorithm. However, we should consider the fact that hospitals have just started to collect more data. We hope that we are seeing the beginning of a new trend of much better and more robust data collection. In the next steps of algorithm development, we will investigate other signal processing techniques such as Hilbert transforms to exploit the nonstationary behavior of the signal and hence seek to further improve the algorithm performance.

Mathematical modeling of the ET intubation is very valuable clinically since it is the first necessary step in automatic detection of tube malpositioning (i.e., inadvertent supraglottic ETT placement or mainstem intubation), which may have life-threatening consequences. Future directions of our work will focus on integrating such mathematical modeling and validating the algorithm on prospective data. Eventually, we aim to implement the algorithm in real-time using the data collection capabilities currently in place at CHOP.

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