Computerized ventilator data selection: artifact rejection and data reduction

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Abstract

Objective: To determine acceptable strategies for automated data acquisition and artifact rejection from computerized ventilators using the Medical Information Bus. **Design:** Medical practitioners were surveyed to establish 'clinically important' ventilator events. A prospective study involving frequent data collection from ventilators was also conducted. **Subjects:** Data from 10 adult patients were collected every 10 seconds from a Puritan Bennett 7200A ventilator for a total of 617.1 hours. **Interventions:** Twelve different computerized data selection and artifact algorithms were tested and evaluated. **Measurements and Main Results:** Data derived from 12 data selection algorithms were compared with each other and with data manually charted by respiratory therapists into a computerized charting system. Ventilator *setting data* collected by the algorithms, such as F_{IO_2} , reduced the amount of data collected to about 25% compared to manually charted data. The amount of data collected for *measured parameters*, such as tidal volume, from the ventilator had large variability and many artifacts. Automated data capture and selection generally increased the amount of data collected compared to manual charting, for example for the 3 minute median the increase was a modest 1.2 times. **Conclusion:** Computerized methods for collecting ventilator *setting data* were relatively straightforward and more efficient than manual methods. However, the method for automated selection and presentation of observed *measured parameters* is much more difficult. Based on the findings and analysis presented here, the authors recommend recording ventilator *setting data* after they have existed for three minutes and *measured parameters* using a three minute median data selection strategy. Such an algorithm rejected most artifacts, required minimal computational time, had minimal time-delay, and provided clinically acceptable data acquisition. The results presented here are but a starting point in developing automated ventilator data selection strategies.

Introduction

Computerization of patient records is an essential technology for improving the quality and efficiency of patient care [1–3]. Many ventilators today are controlled by microprocessors and have digital displays and outputs that can store data into the computerized patient record. Unfortunately, the strategies about which data should be recorded and how to eliminate artifacts from ventilator data have not been elucidated [3–8]. Therefore, we undertook studies to determine acceptable strategies for data acquisition and artifact rejection from computerized ventilators.

In the modern ICU it is common for the patient to be connected to several computerized monitoring devices, such as bedside physiological monitors, pulse oximeters, electrocardiograms (ECG), intravenous (IV) pumps, and ventilators. The data collected from these bedside devices provide an important basis for clinical decision-making. However, medical practitioners must simultaneously acquire, interpret, act on, and record data from each of these devices. In most ICU situations, data are handwritten or in some cases may later be manually entered into a computerized patient record. Twenty-five to 30% of a medical practitioner's time is spent doing paperwork [9]. Data entry errors and time delay errors occur when data are man-

Figure 1. Illustration of inconsistent manual F_iO_2 setting entry.

- A. Respiratory Therapist 'manual' charting did not show that F_iO_2 was set at 100% for 5 minutes.
- B. Both manual and automated charting showed that F_iO_2 was set at 100% for 18 minutes.
- C. Manual record did not show that F_iO_2 was set at 100% for 33 minutes.
- D. F_iO_2 was changed from 60% to 40% at time 16:54, but it was not charted manually until 20:00.

entry of inspired oxygen percentages ($F_{I}O_2$). Earlier investigators have shown that data entry mistakes increase when information is passed through several persons prior to being received by the ultimate decision maker [10].

Recently, McDonald and Hammond have recommended standard formats for exchanging electronic data between computer systems for inclusion into the computerized medical record [11]. In addition the American Medical Informatics Association has proposed standards to help make the computerized medical record a reality [12]. Unfortunately, for ICU patients, each monitoring device or patient support device like a ventilator, is manufactured by a different vendor, and each vendor has their own data communication strategy [13–21]. To facilitate automatic data acquisition from these multiple devices, a standardized Medical Information Bus (MIB) has been proposed and

Table 1. Summary of questionnaire findings

Medical Practitioner	What kind of respiratory care data should be entered?	
	Ventilator <i>setting</i>	<i>measured</i> Ventilator Data
1. Physician (Pulmonary)	1. Every change AND 2. Every 2 hours	1. Median value every 2 hours 2. Dramatic changes (A)
2. Respiratory Care Supervisor	1. Every change	I/E: average every hour TVC: average every 10 minutes MR: average every 30 minutes PeakP: average every 10 minutes MeanP: average every 10 minutes; etc
3. Respiratory Care Supervisor	1. Every change AND 2. At beginning of each shift	1. Dramatic changes (A) if persists longer than 30 to 60 seconds AND 2. Average of every 2 hours
4. Respiratory Care Supervisor	1. Every change, AND 2. Every 2 hours	1. Every 2 hours: average of last 3 breaths AND 2. Dramatic changes: ± 5 cmH ₂ O for MeanP ± 10 cmH ₂ O for PeakP ± 5 bpm for MR
5. Respiratory Care Therapist	1. Every change AND 2. 10–20 minutes after any <i>setting</i> change AND 3. Every 2 hours	1. Every 2 hours: average of 3 minutes 2. 10 to 20 minutes after <i>setting</i> change
6. Respiratory Care Therapist	1. Every change AND 2. Every shift	1. Every 2 hours
7. Critical Care Nurse	1. Every change AND 2. A blood gas draw OR 1. At an initial set-up AND 2. Every 12 hours	1. Record a 'representative' (B) number every 2 hours 2. Ignore 'non-steady' states such as disconnection, suctioning, turning

A. 'dramatic' was not specified B. 'representative' was not specified

is being standardized by the Institute of Electrical and Electronic Engineers (IEEE) [13–18]. The IEEE 1073 standard for the MIB is being established so that all hospitals and vendors can use a common data format and easily communicate with multiple bedside devices [15,16]. MIB handles issues unique to the medical data communications environment such as the need for automatic device recognition when a new device is attached to the patient [21]. The IEEE MIB standard's group seeks development of standards for vendor independent interconnection of medical devices and computer systems for the intensive care unit [17]. The goal of the MIB standard is to avoid the present incompatibility of medical devices from different vendors. However, according to some sources, [18] manufacturers and hospitals are still not prepared to adapt the changes required by the newly standardized MIB. Recent work by Oniki and colleagues has shown the difficulty of recording pulse oximetry and vital signs data from critically ill patients [19, 20].

To determine if there were problems with data collection from computerized ventilators, pilot data acquisition experiments were conducted at LDS Hospital in Salt Lake City, Utah using a prototype MIB. These pilot studies quickly showed that the amount of data available from a ventilator could overwhelm almost any computerized patient record system. From a single patient on a Puritan Bennett 7200A ventilator for a 24 hour period, the MIB system could acquire 33 parameters for every 10 seconds which results in about 1.5 megabytes of data being generated – an enormous amount of data – about 1/3 of the BIBLE for each day! To put such data acquisition volume into context, earlier work at our institution had shown that only about 20 KBytes per day of data were stored for each ICU patient [10].

Table 2. List of patients whose ventilatory data were collected for the study

No	Hours Data Collected	ICU Location	Diagnosis	Vent Mode Used
1	236.0	Shock/Trauma	ARDS & Sepsis	CMV, F/B
2	89.5	Shock/Trauma	Hypertension, Tachycardia, Dehydration	CMV, F/B, CPAP
3	25.0	Med Surg	Anemia, Thrombocytopenia, Angina	CMV
4	43.0	Shock/Trauma	Renal Colic	CMV, F/B, P/S
5	31.0	Shock/Trauma	Anemia	CMV
6	93.8	Shock/Trauma	ARDS	CMV, F/B
7	25.4	Shock/Trauma	Trauma	CMV
8	24.5	Shock/Trauma	Back Injury, Hypertension	CMV, F/B
9	23.4	Thoracic	Hodgkins Disease, Post Bone Marrow Transplant	CMV
10	25.5	Thoracic	Acute MI	CMV
Total	617.1	Hours		

Note: ARDS = Adult Respiratory Distress Syndrome; CMV = Continuous Mandatory Ventilation; CPAP = Continuous Positive Airway Pressure; F/B = Flow By; P/S = Pressure Support.

Methods

Two strategies were used to help determine a rational strategy for automated data collection from ventilators: 1) Seven medical practitioners were asked to specify what ventilator settings and what measured parameters should be collected (see Table 1), and 2) Data were gathered from 10 different patients from whom data were recorded every 10 seconds to test several data acquisition and selection strategies.

A pulmonary physician, three respiratory therapy supervisors, two respiratory therapists, and a critical care nurse were shown graphical ventilator data collected every 10 seconds from 4 patients (similar to Figure 3). They were asked to identify 'important clinical events' and develop a strategy for recording ventilator setting and measured data.

Surprisingly, these medical practitioners had very different opinions about what ventilator data should be reported in the patient's record. Although today's knowledge and technology in medicine seem to be highly developed, health care providers still rely heavily on personal experience and clinical judgment in their determination of what data to collect and record. However, if the data acquisition task is to be automated, it is essential that health providers establish a set of data collection rules. For example, how often and what kind of data should be acquired, entered, and stored into a computerized patient record [2, 7]?

Because of the wide disparity of opinions extracted from the medical practitioners, a careful scientific study of automated data collection strategies from

ventilators was undertaken. The Medical Informatics research team at LDS Hospital has implemented a pilot MIB system which can communicate with different bedside devices and to the HELP system [21–24]. The HELP computerized hospital information system routinely provides clinical, administrative, financial, and decision support functions. Computerized patient data are stored in a centralized database. Figure 2 shows a block diagram of the MIB attached to several bedside devices for an ICU patient. Unfortunately, current IEEE 1073 MIB standards include neither recommendations for artifact rejection nor data reduction strategies [15, 16].

Data were collected every 10 seconds from 10 different patients on ventilator support for a total of 617.1 hours (25.7 days). These patients were selected from our Shock/Trauma ICU, the Thoracic (Post Open Heart) ICU and a step-down Medical-Surgical ICU (See Table 2) at LDS Hospital. Data from all 10 patients were combined to generate a library of patient data collected in the clinical environment (approximately 38 megabytes or about 1.5 megabytes per day). Table 2 lists the time frames the data were collected from each patient. The resulting patient database was stored on a mini-computer located in the ICU and then transferred to a VAX 3100 M38 workstation at the University of Utah Department of Anesthesiology laboratory for analysis. Data from the Puritan Bennett 7200A ventilator were sampled every 10 seconds. The 10 seconds sampling interval was selected because:

Table 3. MIB Parameters

No	MIB Name	Description	Typical Range		Units
			Lower	Upper	
Ventilator setting					
1	MODE	Ventilation Mode setting			
2	Rate	Machine respiratory rate setting	0.5	70.0	bpm
3	TV	Machine tidal volume setting	100	2500	ml
4	PIF	Peak inhaled flow setting	10.0	120.0	lpm
5	F _I O ₂	Oxygen concentration setting	21	100	%
6	Sens	Sensitivity setting	0.5	20.0	cmH2O
7	PEEP	PEEP setting	0.0	45.0	cmH2O
8	Plateau	Plateau time setting	0.0	2.0	second
9	PS	Support pressure setting	0.0	70.0	cmH2O
10	Flow	Flow By: Support flow setting	5.0	20.0	lpm
11	FlowSen	Flow By: Flow sensitivity setting	1.0	10.0	lpm
measured ventilator data					
12	PeakP	Current patient peak airway pressure	0	120	cmH2O
13	MeanP	Current patient mean airway pressure	0	120	cmH2O
14	PlatP	Current patient plateau pressure	0	120	cmH2O
15	I/E	Current patient I/E ratio			
16	TVS	Current patient spontaneous tidal volume	100	2500	ml
17	TVC	Current patient corrected tidal volume	100	2500	ml
18	SR	Current patient spontaneous respiratory rate	0.5	70.0	bpm
19	AR	Current patient assisted respiratory rate	0.5	70.0	bpm
Other Puritan Bennett 7200A Variables (Not entered manually)					
20	TVU	Uncorrected tidal volume	0.0	2.5	liter
21	TVP	Current patient tidal volume (=TVS or TVC)	0.0	2.5	liter
22	MV	Current patient minute volume (=TVC* MR)	0	60	liter
23	SV	Current patient spontaneous minute vol (=TVS* SR)	0	60	liter
24	HP	High pressure limit alarm setting	10	120	cmH2O
25	LP	Low inspiratory pressure alarm setting	3	99	cmH2O
26	AS	Low PEEP/CPAP alarm setting	0	45	cmH2O
27	TVA	Low exhaled tidal volume alarm setting	0.0	2.5	liter
28	LMA	Low exhaled minute volume alarm setting	0	60	liter
29	RA	High respiratory rate alarm setting	0	70	bpm
30	SC	Static mechanics compliance volume			
31	Time	Current time			
32	NOW	‘NOW-BUTTON’ pushing flag			
33	SEC	Elapsed time – no response to DCC query			

1. Physiologically transient changes that lasted less than 10 seconds were not considered 'clinically important',
2. An earlier pilot study done by one of the authors (TDE) showed that filtering frequencies above 0.01666 Hz (1 minute) eliminated only a tiny part of the 'real' signal but effectively removed artifacts [25].

Only 19 of the 33 parameters available from the Puritan Bennett 7200A ventilator were logged because they were the parameters used with the currently operational

computerized respiratory care charting system at LDS Hospital [9]. As a result, the same 19 parameter data set was collected for our experimental use. Table 3 lists definitions and abbreviations of these parameters. Ventilatory data collected for the study were categorized into two classes: machine *settings* and *measured* ventilator parameters. Only *measured* ventilator data were processed for artifact rejection. The machine *settings* were NOT processed with an artifact rejection algorithm because:

Table 4. Six algorithm strategies used to evaluate artifact rejection (Example for 3 minutes → 18 data points)

No	Algorithm	Description
1	Moving Average	$Y(t) = [X(t-17) + X(t-16) + \dots + X(t)]/18$
2	Moving Median	$Y(t) = \text{Median value of sorted last 18 } X(t)$
3	Moving Exponential, W-1	$Y(t) = [X(t-17)*e^{(t-17)} + \dots + X(t)*e^{(t)}]/W1$
4	Moving Exponential, W-2	$Y(t) = [X(t-17)*e^{(t-17)/17} + \dots + X(t)*e^{(t)/17}]/W2$
5	LOWESS	Processed every hour of data by LOWESS Algorithm
6	Moving LOWESS	Processed every hour of data (total 360 data points) by LOWESS. Print 301th or 330th data point to the output. Discard first 5 minutes' data from the moving window then take next 5 minutes of data and repeat the process

$X(t)$ = raw input at time t and was collected every 10 seconds.

$Y(t)$ = processed output at time t .

$W1$ = weighing method number 1 = $e^{(t-17)} + \dots + e^{(t)}$

$W2$ = weighing method number 2 = $e^{(t-17)/17} + \dots + e^{(t)/17}$

1. *Settings* changes occur infrequently when compared with breath by breath *measured* ventilator data and,
2. Every change in machine *setting* is important to the patient's record and probably should not be eliminated. However, we later decided to record and report only machine *setting* changes that lasted for at least three minutes.

Six methods were tested to reject *measured* ventilator parameters' artifacts: a moving average low pass filter, moving exponential weighted filters (two sets of weights were evaluated), a moving median; a regression technique known as Locally Weighted Regression (LOWESS), a method used to smooth weather forecasting data [26], and also a moving LOWESS was used (See Appendix A for a brief description of the LOWESS methodology). Table 4 lists the six algorithms used.

A major objective of our study was to determine how and what data should be collected and stored as 'clinically important events.' Measured parameters that lasted longer than a specified 'time window' (T_{window}) were recorded. Two time windows were compared: one minute and three minutes. Thresholds for entering ventilator *settings* and *measured* parameters into the computerized patient record are noted in Table 5. These thresholds were suggested by one of the directors of respiratory care.

Historically, when a respiratory therapist changed the mode *setting* of the ventilator, all the relevant *settings* and *measured* values were also recorded. Consequently, data collection algorithms were initially designed to report all measurement values within one minute after the mode changed independent of the thresholds and the length of the time window.

The six algorithms noted in Table 4 and two time windows were used. Thus, a combination of 12 artifact rejection and data reduction algorithms noted in Table 6 were tested. All 617.1 hours of data were tested with all 12 algorithms. The results obtained were also compared with manually charted data entered into the HELP computerized patient records [9, 27]. The notes in Table 7 indicate that on the average respiratory therapists manually recorded ventilator *setting data* every 3.33 hours and measured *ventilator* parameters every 2.57 hours.

Results

Because of space limitations, only part of the data are shown. Figure 3 through 6 show short time segments from one patient for tidal volume obtained from four of the algorithms. The Figures overlay the results from the 10 second automated data collection, data from manual therapist entry and results of the processing algorithm. Figure 3 shows the original 10 second MIB data, the data manually entered and the result of using a moving average algorithm with a time window of one minute. Note that there were several 'zero' tidal volumes reported from the ventilator, even though such breaths likely did not occur and were probably a result of MIB to ventilator interface problems. For Figure 3, the moving average algorithm (moving average, $T_{window} = 1$ minute) reported 18 'events' while therapists logged 13 events. It can be seen from the plot that the automated data selection algorithm gave 'more typical or representative' indications of the measured parameter for the specific time interval than did the manual entered data when compared with the 'raw' 10

Table 5. MIB Parameter data selection thresholds

No	MIB Name	Thresholds
<i>A. Ventilator setting</i>		
1	MODE	Every change
2	Rate	Every change or 1 minute after MODE was changed
3	TV	Every change or 1 minute after MODE was changed
4	PIF	Every change or 1 minute after MODE was changed
5	F _I O ₂	Every change or 1 minute after MODE was changed
6	Sens	Every change or 1 minute after MODE was changed
7	PEEP	Every change or 1 minute after MODE was changed
8	Plateau	Every change or 1 minute after MODE was changed
9	PS	Every change or 1 minute after MODE was changed
10	Flow	Every change or 1 minute after MODE was changed
11	FlowSen	Every change or 1 minute after MODE was changed
<i>B. measured ventilator data</i>		
12	PeakP	(absolute change > 10 cmH ₂ O AND 3 < PeakP < 120 cmH ₂ O OR 1 minute after every MODE change)
13	MeanP	(absolute change > 5 cmH ₂ O AND 3 < MeanP < 120 cmH ₂ O OR 1 minute after every MODE change)
14	PlatP	(absolute change > 5 cmH ₂ O AND 3 < PlatP < 120 cmH ₂ O OR 1 minute after every MODE change)
15	I/E	% change > 25% OR 1 minute after every MODE change
16	TVS	(% change > 10% AND absolute change > 100 ml AND 100 ml < TVS < 2500 ml OR 1 minute after every MODE change)
17	TVC	(% change > 10% AND absolute change > 50 ml AND 100 ml < TVC < 2500 ml OR 1 minute after every MODE change)
18	SR	(% change > 10% AND absolute change > 5 bpm AND 0.5 bpm < SR < 70 bpm (bpm = breaths per minute) OR 1 minute after every MODE change)
19	AR	(% change > 10% AND absolute change > 2 bpm AND 0.5 bpm < SR < 70 bpm OR 1 minute after every MODE change)

second MIB data. The respiratory therapist entered a corrected tidal volume of 1,100 ml at 5:00 and 20:30. A corrected tidal volume of 1,100 ml may have occurred and not been recorded since the MIB system queried data from the ventilator only every 10 seconds (every 2 to 5 breaths depending on respiratory rate). However, it is unlikely that any 1,100 ml values actually occurred. More likely the therapist recorded the values at a slightly different time. In any event, the manual data entry results were not ‘representative.’ The plot shows the average corrected tidal volume ranged from 700 ml to 1000 ml over the entire 24 hour time period.

Figure 4 shows the comparison of original 10 second MIB corrected tidal volume, manual data entry, and algorithm data selection made using the moving LOWESS with a time window of one minute. Figure 4 shows that the moving LOWESS algorithm rejected more artifacts than did the moving average (Figure 3). The LOWESS methodology reported only three ‘events’ and provided a good picture of patients’ corrected tidal volume.

Figure 5 shows the comparison of original 10 second MIB corrected tidal volume, manual data entry and algorithm selected data based on a moving median with a time window of one minute. Compared to the

Figure 3. Automated Charting Algorithm: Moving average with a time window of 1 minute. The MIB system collected 8,640 Tidal Volume data points during a 24 hour time period, while the automated charting algorithm reported 18 important events and respiratory therapists 'manually' logged only 13 events.

Figure 4. Automated Charting Algorithm: Moving LOWESS with a time window of 1 minute. Comparing to Figure 3, the moving LOWESS algorithm rejected more of the artifact than did the moving average method. The plot gives a very good picture of this patient's tidal volume. The automated charting algorithm reported only 3 important events the same 24 hour period.

method shown in Figure 3 the moving median algorithm rejected more artifacts and reported only seven 'events.' Finally, Figure 6 shows automated data selection using a moving median with a time window of three minutes. This algorithm reported only five 'events' yet provided a good picture of patients' mean corrected tidal volume. Although some data selection algorithms reported fewer events than manual data entry, from these figures (Figure 3 to 6) it can be seen that automated data selection seemed to provide more 'representative' data than did the manual data entry.

Since there was no 'gold standard' with which to compare the data appropriate for being recorded in the patient record it was difficult to make any statistical

Figure 5. Automated Charting Algorithm: Moving median with a time window of 1 minute. Compared to Figure 3 and 4, the moving median algorithm rejected more artifact than moving average (Figure 3) but less than moving LOWESS (Figure 4). This algorithm reported only 7 important events during the same 24 hour period.

Figure 6. Automated Charting Algorithm: Moving median with a time window of 3 minutes. This figure shows a moving median time window of 3 minutes. Five important events were reported for the same 24 hour time period.

judgement about the adequacy of the automated data selection algorithms. However, it became apparent to the authors after reviewing records such as those shown in Figures 3 through 6, that the manual data selection and entry by respiratory therapists for *measured* parameters was not adequate. The manually entered results were not representative and seemed to be chosen for the few moments the therapist was at the patient's bedside. Also several manually entered results seemed to show that these data points were not gathered nor entered into the computer at the time the values were said to have occurred.

Table 7 lists the total number of 'events' reported by the respiratory therapists (manual data entry) and by the automated data selection algorithms. Table 7 shows that about 25% (22.7 to 27.7%) of the machinesetting

Table 6. Definitions and abbreviations of algorithms

No	Algorithm Abbreviation	Algorithm Definition	Time window
1	average-1m	Moving average	1 minute
2	average-3m	Moving average	3 minute
3	median-1m	Moving median	1 minute
4	median-3m	Moving median	3 minute
5	exp-1-1m	Moving Exponential Weighted Average Forgetting Factor = $e(t-n)$	1 minute
6	exp-1-3m	Moving Exponential Weighted Average Forgetting Factor = $e(t-n)$	3 minute
7	exp-2-1m	Moving Exponential 1 minute Weighted Average Forgetting Factor = $e(t-n)/n$	
8	exp-2-3m	Moving Exponential Weighted Average Forgetting Factor = $e(t-n)/n$	3 minute
9	LOWESS-1m	LOWESS	1 minute
10	LOWESS-3m	LOWESS	3 minute
11	m-LOWESS-1m	Moving LOWESS	1 minute
12	m-LOWESS-3m	Moving LOWESS	3 minute

Table 7. Total 'events' reported by different data selection algorithms

Algorithm	Machine settings			Measured ventilator data		
	Total data points	Percent (%) compared to		Total data points	Percent (%) compared to	
		Raw MIB Data ¹	Manual Data Entry ²		Raw MIB Data ³	Manual Data Entry ⁴
average-1m	564	0.02	27.7	4,413	0.25	230.3
average-3m	477	0.02	23.4	2,643	0.15	137.9
median-1m	564	0.02	27.7	3,987	0.22	208.1
median-3m	477	0.02	23.4	2,315	0.13	120.8
exp-1-1m	564	0.02	27.7	5,689	0.32	296.9
exp-1-3m	477	0.02	23.4	1,561	0.09	81.5
exp-2-1m	564	0.02	27.7	4,640	0.26	242.2
exp-2-3m	477	0.02	23.4	2,574	0.33	134.3
LOWESS-1m	562	0.02	27.6	1,575	0.09	82.2
LOWESS-3m	477	0.02	23.4	1,264	0.07	66.0
m-LOWESS-1m	549	0.02	26.9	1,603	0.09	83.7
m-LOWESS-3m	462	0.02	22.7	1,251	0.07	65.3
Raw - 10 Sec Data	2,443,320	100.0	1,198.91,776,960	100.0	927.4	
Manual data entry	2,038	0.08	100.0	1,916	0.11	100.0

1. Percentage compared to raw MIB data = Total data points reported by each algorithm divided by 2,443,320

2. Percentage compared to manual data entry = Total event reported by each algorithm divided by 2,038

3. Percentage compared to raw MIB data = Total data points reported by each algorithm divided by 1,776,960

4. Percentage compared to manual data entry = Total data points reported by each algorithm divided by 1,916

5. Average time between manual recording of *setting* data = 200 minutes = 3.33 hours

6. Average time between manual recording of *measured* parameters = 154 minutes = 2.57 hours

Table 8. CPU time and time-delay used for each algorithm

Algorithm	CPU time		Time-delay	
	Total seconds	Average μ seconds	<i>Measured Ventilator Data</i> (minutes)	<i>Machine Settings</i> (minutes)
average-1m	233	55	1	1
average-3m	233	55	3	3
median-1m	231	55	1	1
median-3m	231	55	3	3
exp-1-1m	239	57	1	1
exp-1-3m	239	57	3	3
exp-2-1m	239	57	1	1
exp-2-3m	239	57	3	3
LOWESS-1m	822	195	61	1
LOWESS-3m	822	195	63	3
m-LOWESS-1m	3,802	901	1	1
m-LOWESS-3m	3,802	901	3	3

data would have been recorded compared to the manual data entry. Automated data selection algorithms reported less than 0.02% of the raw MIB data for machine *settings*. For *measured* ventilator data, algorithms using LOWESS for artifact rejection (LOWESS-1m, LOWESS-3m, m-LOWESS-1m, m-LOWESS-3m) reported about two thirds (65.3% to 83.7%) of the records compared with manual data entry. However, other algorithms reported from 1.20 to 2.97 MORE records than did manual data entry except for the algorithm that used the exponential weighted average with a time window of three minutes which was only 81.5%.

Table 8 lists the amount of VAX station 3100 M38 CPU time in μ seconds that were used to process each algorithm for the 617.1 hours of data and the average CPU time used to process each data point. Table 8 also lists the 'time-delay', in minutes, resulting from the moving window processing mechanism.

Conclusion and recommendations

Using a one minute time window for *measured* ventilator data and a three minute time window for machine *settings* further reduces the number of events report by the algorithm yet did not adversely affect the accuracy. From our experimental results it was concluded that:

1. Original MIB data collected from the ventilator at 10 second intervals can be selected and 'clinically important events' can be reliably recorded by automatic methods.
2. Data selection algorithms using moving average, moving median, all but one moving exponentially weighted algorithm and conventional LOWESS reported more information than the therapist on *measured* data and report less information on all machine *setting* data recording.
3. The moving average algorithms often retain some of the characteristics of original artifact if the artifacts contain values that were greatly different from the average values. The moving exponentially weighted (exp-1-1m and exp-1-3m) algorithms tend to keep more original values, an artifact might be weighted 63% of its value. The moving median was found to be the best choice if the patient's condition was not stable and there were artifacts in the data – the usual clinical state. Also, the median approach does not generate a value that 'never occurred' while averaging algorithms frequently do.
4. Data selection algorithms using LOWESS or moving LOWESS reported the fewest events. These algorithms may be the best choice for data reduction. However, these computations cost much more computer time. Because of long computational times, these algorithms also cause excessive time delays.
5. On the issues of timeliness, data entry errors and time saving of data acquisition by automated data selection algorithms the following conclusions were drawn:
 - A. *Timeliness* Observations made in ICUs showed that during their busy times some respiratory

therapists often took brief notes on paper and then ‘back-charted’ data when they had time to chart. One respiratory therapist even ‘back-charted’ data that were three hours old (see Figure 1). Currently ‘timely’ charting is not absolutely required at LDS Hospital, and many therapists manually ‘back-chart’ data. In contrast, all the algorithms report ‘events’ with relatively short time-delays (see Table 8).

B. Data Entry Errors Because the automatic data selection algorithms used a threshold table for all the respiratory parameters, inconsistencies in recording respiratory data could also be avoided. ‘Not representative’ *measured* ventilator data such as the corrected tidal volume in Figure 3 could be also minimized.

C. Time Saving Between 25 and 30% of a respiratory therapist’s time is spent on paperwork [9]. An automated data selection algorithm could dramatically reduce this time and respiratory therapists could spend more time evaluating patients.

Recommendations

Based on the experiments performed, an optimum algorithm for automated ventilator data selection for adults is:

Sampling frequency:

- Query ventilator every 10 seconds.

For machine *settings*:

- Report every machine *setting* change if it lasts longer than 3 minutes.
- For ‘pause times’ during which time the therapists record plateau pressures, the therapist should be asked to push the MIB ‘now-button’ and send the ‘pause time’ data.

For *measured* ventilator data:

- Process original MIB collected data with moving median, which will
- Store changes greater than the thresholds (noted in Table 5) that lasts over 3 minutes.

Peak Airway Pressure change > (10 cmH₂O AND 10%)

Mean Airway Pressure change > (5 cmH₂O AND 10%)

Spontaneous Tidal Volume change > (100 ml AND 10%)

Corrected Tidal Volume change > (50 ml AND

10%)

Spontaneous Rate change > (5 bpm AND 10%)

Machine Assisted Rate change > (2 bpm AND 10%)

Plateau Pressure → every change

Measured I/E Ratio change > 25%

Ventilator and other ICU device manufacturers should be encouraged to take a more careful look into their methodology for artifact rejection and transmission of non-representative data. Eventually the MIB and data selection methodologies should be built into every bedside monitor and ventilator. The above noted recommendations are given as a starting point. These recommendations should be carefully tested and validated. The algorithms will require changes for infants and children. If we are to ever achieve a goal of having the computer assist with medical decision-making, we must first work out the problems of better, more timely computerized data acquisition [28–33].

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Appendix A Explanation of LOWESS Methodology

‘Locally weighted regression or LOWESS, is a way of estimating a regression surface through multivariate smoothing procedure, fitting a function of the independent variables locally and in a moving fashion analogous to how a moving average is computed for a time series.’ [26] The dependent variable is smoothed as a function of the independent variable (in our case time) in a moving fashion analogous to how a moving average is computed for time series. Smoothing by local fitting is actually an old idea that is deeply buried in time series methodology. Locally weighted regression can provide estimates of surfaces, but we only used it in two dimensional space. For example an estimate of $g(x)$ at any value of x . Let q be an integer, where $1 < q < n$. The estimate of g at x uses q observations whose x_i values are close to x . Each point in the neighborhood is weighted according to its distance from x ; points close to x have large weight, points farther away from x have a smaller weight. Since each x point must have this weighting function, usually a linear or quadratic function applied to it, the process is very computer intensive. Details of several strategies and even optimized strategies for computation are found in reference 26.

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