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SYSTEMS-LEVEL QUALITY IMPROVEMENT

Reliable Collection of Real-Time Patient Physiologic Data from less Reliable Networks: a "Monitor of Monitors" System (MoMs)

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Abstract Research and practice based on automated electronic patient monitoring and data collection systems is significantly limited by system down time. We asked whether a triple-redundant Monitor of Monitors System (MoMs) to collect and summarize key information from system-wide data sources could achieve high fault tolerance, early diagnosis of system failure, and improve data collection rates. In our Level I trauma center, patient vital signs(VS) monitors were networked to collect real time patient physiologic data streams from 94 bed units in our various resuscitation, operating, and critical care units. To minimize the impact of server collection failure, three BedMaster® VS servers were used in parallel to collect data from all bed units. To locate and diagnose system failures, we summarized critical information from high throughput datastreams in real-time in a dashboard viewer and compared the before and post MoMs phases to evaluate data collection performance as availability time, active collection rates, and gap duration, occurrence, and categories. Single-server collection rates in the 3-month period before MoMs deployment ranged from 27.8 % to 40.5 % with combined 79.1 % collection rate. Reasons for gaps included collection server failure, software instability, individual bed setting inconsistency, and monitor servicing. In the 6-month post MoMs deployment period, average collection rates were 99.9 %. A triple redundant patient data collection system with real-time diagnostic information summarization and representation improved the reliability of massive clinical data collection to nearly 100 % in a Level I trauma center. Such data collection framework may also increase the automation level of hospital-wise information aggregation for optimal allocation of health care resources.

Keywords Data collection · Vital signs · Triple redundant · Datastream · Real-time · Diagnosis

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Introduction

Advances in computer hardware and medical sensor technology facilitate collection of large quantities of physiologic patient data in real-time. Data ranging from routine intermittent observations to high fidelity waveforms can be recorded and streamed into monitors for care planning, clinical decision support [1], quality improvement [2], and reduce hospital mortality [3]. With massive storage capability, those data can also be stored as part of the electronic health records (EHRs) for retrospective analyses such as physiological pattern discovering [4, 5] and prediction modeling [6, 7]. The amount and intimacy of the data potentially available for analysis offers an unprecedented view of physiologic subtlety and variability in health and disease. One example is the PhysioBank, a large collection of biomedical databases, which inspires studies in cardiovascular time series dynamics, modeling intracranial pressure for noninvasive estimation, and more [8–11]. Moreover, reliably collected data could make near real-time clinical decision support practical in emergency healthcare or en route care in combat field [12, 13].

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A major limitation to the full exploration of these data is the inevitable gaps in the continuity of the data that occur with system downtime. In advanced analysis and prediction modeling, such gaps create the classic epidemiologic "lost to follow-up" problem. Among other concerns, at a practical level, missing data hinder the application of many statistical analysis methods available in off-the-shelf software [14]. Increasing the reliability of the collecting system becomes more important in modern advanced care monitoring and data collection systems. However, in a busy resuscitation or health-caring environment, collecting more complete data is not the top priority of health providers. Most modern hospitals data collection systems, even if quite advanced and continuously updated, are an assemblage of various, often decentralized systems and devices. Monitoring, management, and quality assessment of such systems is beyond individual human capability, and researchers are beginning to explore ways to do this [15, 16]. Hence, a reliable system that simplifies and automates the collecting process is necessary.

In our Level I regional trauma center, 94 GE-Marquette-Solar-7000/8000® (General Electric, Fairfield, CT) patient vital signs (VS) monitors are networked to provide collection of real time patient VS data streams in 13 trauma resuscitation unit (TRU), 9 operating room (OR), 12 post-anesthesia care (PACU), and 60 intensive care (ICU) individual bed/monitor units. Each patient monitor collects real-time 240 Hz waveforms and 0.5 Hz trends data which are broadcasted via UDP (User Datagram Protocol) through secure intranet to a dedicated BedMaster® server (Excel Medical Electronics, Jupiter, FL) and archived [17]. This process generates approximately 20 million data points/day/bed or roughly 30 terabits/year of data. Physiologic data collected through this system, when they are displayed on the GE Marquette monitor, include electrocardiographic (ECG), photoplethysmographic (PPG), carbon dioxide (CO_2), arterial blood pressure (ABP), and intracranial pressure (ICP), among others. Trends include heart rate (HR), respiratory rate (RR), temperature, oxygen saturation (SPO_2), end-tidal CO_2 (EtCO2), and ICP, among many others.

We asked whether constructing a multiple-redundant "monitor-of-monitors" (MoMs) collection system capable of providing ongoing quality assurance assessments would allow us to increase our collection rates of these various steams. In this study, we presented an architecture of triple redundant patient data collection system with real-time diagnostic information summarization. We demonstrated its usefulness through the comparison of collection rates 6 months before and after the deployment of such system.

Methods

Over a 12-month study period, we assembled and installed the required server hardware, designed and implemented the relevant software, recorded pre-implementation and post-implementation studies of physiologic data collection gaps, and categorized these gaps by time intervals of relevance for quality assurance and human factors review. In the first phase, we assembled the necessary hardware, developed prototype software, and tracked physiologic data collection success in the pre-existing, single-server, system. In the second phase, we tested the prototype MoMs system hardware and software. In the final phase, we implemented the MoMs system in real-time for all 94 individual bed/monitor collection points in our Level I regional trauma center. In both the pre- and post-MoMs deployment phases, we calculated the percentage of gap duration, gap occurrence (average numbers of gap event per bed per month), and identified gap causes.

Triple redundant VS collection system

To minimize the impact of individual server collection failure, we installed three dedicated BedMaster® servers in parallel to simultaneously collect physiologic patient data from the network of patient monitors described above. Figure 1 diagrams the datastreams from multiple individual bed units to three BedMaster® servers arranged in parallel. This triple modular redundancy architecture permits fast switch over time and high system availability [18]. One server is selected as a principle or "backbone" server. When it fails, values from a second sever will fill in. When two servers fail, values from the third one will be used.

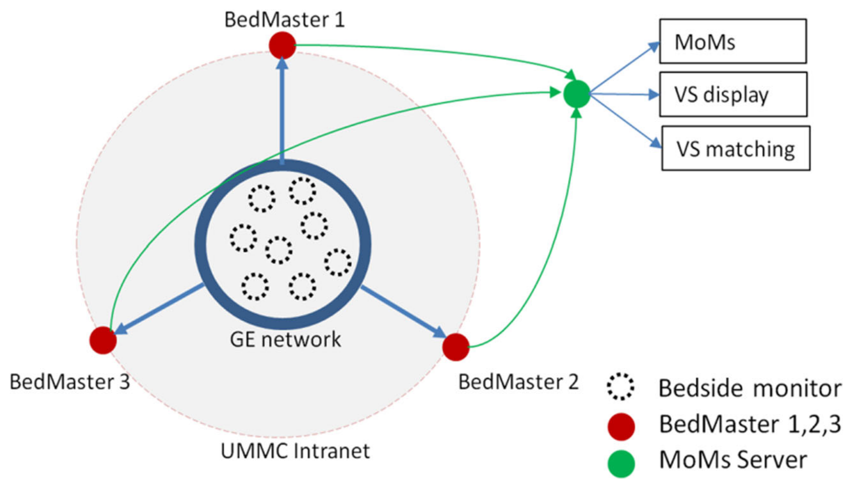
MoMs dashboard viewer

The triple redundant data collection system could increase data availability. However, a tool for fast system diagnosis is still lacking. To address the need for ongoing system status monitoring and real-time presentation critical clinical data, we developed the MoMs information representation layer over the VS collection system. Using the current data collecting architecture and a minimum-instrument approach, we stream the most recent record from the BedMaster® server from each bed to a dedicated data server, the MoMs server (Fig. 1). A high performance database hosts those data items labeled with data server name, bed unit, timestamp, admission status.

The front-end (MoMs Viewer) is designed as a web-based application so that users can access it from any location in the hospital.[1] IP address white-list and user login modules are used for information security. Each bed collection status is summarized and pushed to the MoMs viewer through the Ajax (asynchronous Javascript and XML) techniques every minute. All 94 participating patient bed units are represented by individual cells in each of 3 spread-sheet blocks

[1] A simplified code framework is hosted at https://github.com/shimingyoung/MoMs.

Fig. 1 The MoMs system architecture with triple modular redundancy design using three BedMaster servers



representing one of the three redundant BedMaster® servers. Figure 2 shows a block of the web-based monitoring system corresponding to bedside collections from monitors in the TRU, ORs, and neurotrauma critical care (NTCC), and multi-trauma critical care (MTCC) units. The background color of each cell represents the associated bed's data collection status. Green indicates that the data stream has been alive in the last 5 min. Yellow indicates that the last timestamp from data from that bed/monitor is 5 min to 4 h old and that a problem may exist. Dark red indicates a timestamp gap greater than 4 h and that action should be taken to remedy the problem. Report of an elapsed data collection gap includes the duration of collection failure. Table 2 summarized common indications from the MoMs viewer, which can assist quick system diagnosis, and hence help to reduce data collection failure time.

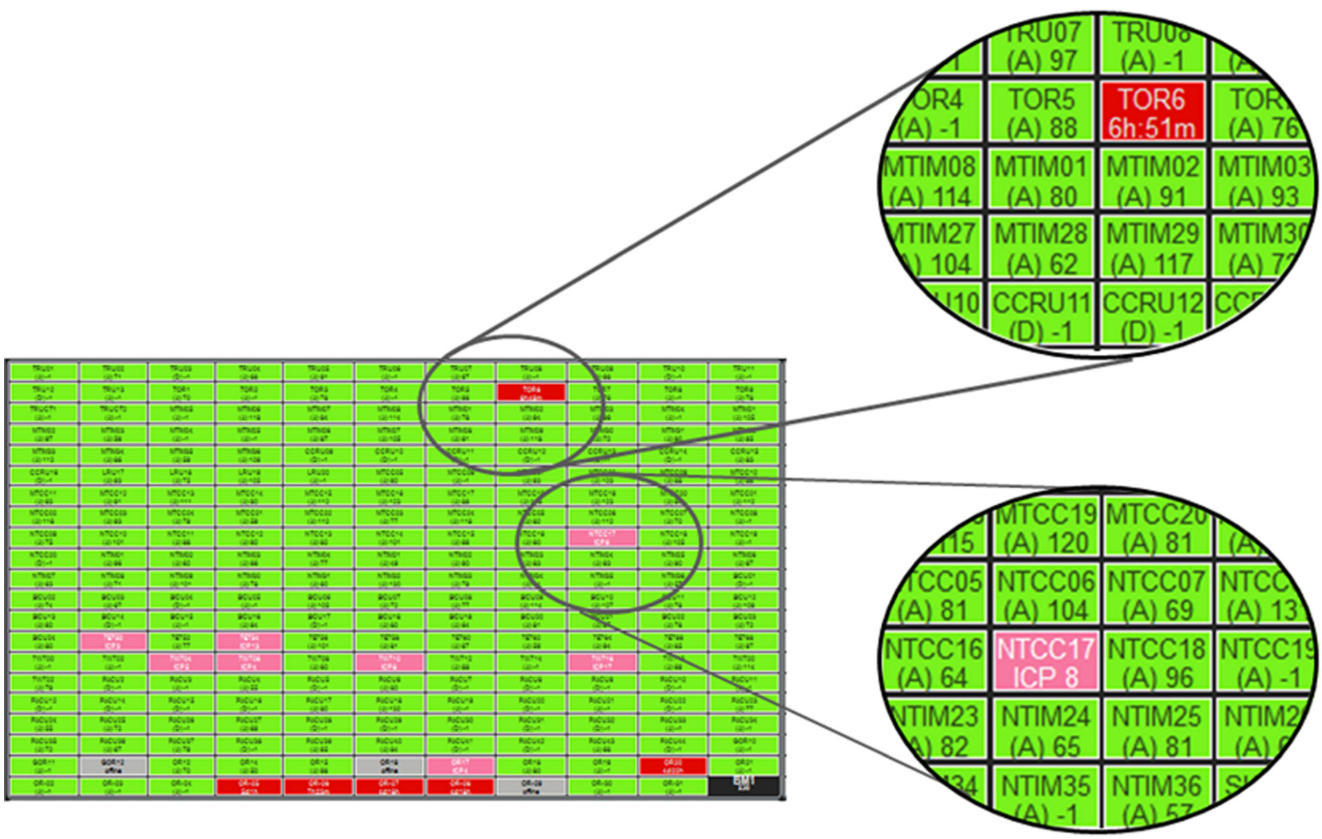


Fig. 2 A portion of MoMs viewer for data collection status. *Green cells* (shown): collection is active (within last 5 min); *yellow* (not shown): collection was active 5 min to 4 h ago; *red* (shown): no data collection has occurred in more than 4 h; *gray* (shown): a bedside collection is offline. In each cell letter "A" means admitted; letter "D" discharged. The pink background cell indicates a patient with an intracranial monitor in place; ICP value appears in *white*

There are different elements in each colored cell to indicate bed unit occupancy. Often, nurses may press a bedside button for admission (A) to or discharge (D) from this bed. This allows for a cross-check on potential causes for information gaps such as the device being temporarily inoperable or no patient being monitored. In addition, bed occupancy can be verified by real-time physiological values, such as HR. It can be used as a second evidence for us to infer if a bed unit is currently occupied by a patient. If one bed unit is offline, the gap between now time to its last reported time will be shown. Figure 2 shows one such example in the unit OR-6, which was highlighted in a red cell with a time gap of 6 h and 51 min.

The easy configuration of the MoMs dashboard viewer also allows it to be used for identifying and displaying clinical information of special research interest. For example, intracranial pressure (ICP) monitoring is an important VS for traumatic brain injured patients and is not often collected due to its invasive nature. To receive early notification of ICP-monitored cases, the MoMs viewer can extract ICP data from all bed/monitor units data streams and display these data using a pre-defined color code. In Fig. 2, those pink cells with white bold font text show real-time ICP values from the corresponding bed/monitor units. For example, at the time we viewed the MoMs system, the unit NTCC-17 was monitoring ICP with instant value of 8 mmHg.

VS collection gap analyzer

To provide an at-a-glance view of the status of data collection, we visualized the collection gap patterns for all three data servers (Fig. 3). These patterns may be associated with individual server collection system failure (Pattern A); individual bed collection failure (Pattern B) and individual patient monitor disconnection from the server (Pattern C). The analyzer also provides a visual display of how the triple redundant system can be used to enhance the overall data collection rate. Data from the three servers can be aligned using the accumulated internal clock drift by using the timestamp and also the shape of the various waveforms. One of the servers is established as the "backbone" server. Missing data are filled in from parallel data from one of the other servers. In Fig. 3, "TRU 01–04" indicates individual patient bed/monitor units located in the TRU. Interruption in the wide blue (BedMaster 1), pink (BedMaster 2) or green (BedMaster 3) bars indicates that that server is down. The narrow red bars within each server bar represent HR values being actively collected and present in the data stream.

Parsing and visualization of the large volume of numeric data are enabled by highly optimized and parallel operations. Aggregating data over longer durations (a week) and from multiple units (13 bed units in the TRU) for all three servers require processing roughly 16 million data points.[2] To present these data efficiently, we pre-processed historic data collected by three servers into the Matlab (R2014a, MathWorks, Boston, MA) default data format for high performance on disk input/ouput. [19] Using vectorized code, we organized time-aligned data into matrices and visualize millions of data point in 2 ~ 3 s for weekly-data diagnosis.

Results

The active study period for this work was February 2013 through January 2014. The testing phase focused on the TRU, the most active site in our advanced trauma care system. The final deployment phase incorporated all 94 bed units in our current system. According to the hospital trauma registry and ADT (Admission/Discharge/Transfer) records during this study period, there were total 8719 adult patients stayed in hospital, with average 3.8 days of hospital stay.

During the 3 month pre-MoMs developmental phase, after the installation of the three dedicated servers but before their being linked through the MoMs software as a redundant system, collection rates range from each individual dedicated server were 27.79 % to 40.49 %. After the installation of the triple-redundant server system but before the installation of the viewer system, the total physiologic data collection rate improved to 79.13 % (Table 1). The overall missing collection rate (gap) was 20.87 %. Most of this was due to collection gaps of >4 h (18.02 % of potential collection time or 1.62 times/bed/month). Five minute – 4 h collection gaps were recorded 0.13 % of potential collection time or 0.6 times/bed/month. Reasons recorded for collection gaps included individual collection server failure, software instability, individual bed setting inconsistency, and clinical engineering servicing of patient monitors. During this period, no collection failure notification system was in place.

In the 6-month post-MoMs deployment period, after the installation of the collection failure notification system, single server collection rates ranged from 87.05 % to 95.54 % and the triple redundant system achieved 99.88 % total collection rate. Collection gaps were characterized as 5 min – 4 h (yellow), 0.01 % or 0.08 times/bed/month; and >4 h (red), 0.11 % or 0.02 times/bed/month (Fig. 4).

Individual server contributions are also shown in Table 1. In the pre-MoMs phase, the individual servers had relatively low alive rates, however, the combined up time was about 80 %. In the post-MoMs deployment phase, after the activation of the information summary and early notification viewers, individual servers' up time and the combined system up time improved

[2] It is estimated by assuming the data are of 2 s resolution. 1800 point/h × 24 h × 7 days × 13 units × 4 variables =15.7 million data points.

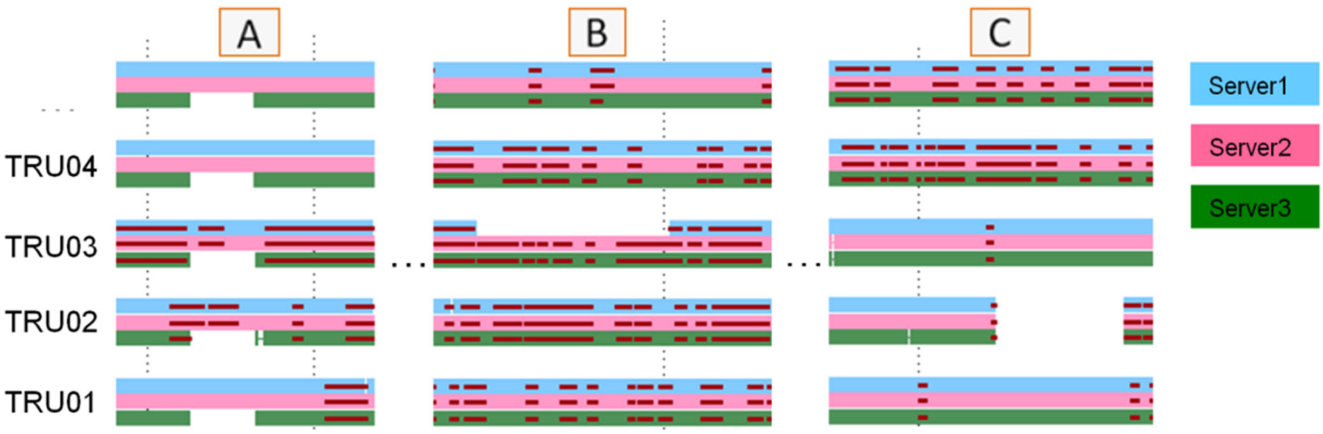


Fig. 3 Three patterns of component failure visualized by the "Collection Gap Analyzer" for data gathered in the triple modular redundancy system. Pattern A: server 3 was offline while the other two were alive; Pattern B: all servers are alive but one bed unit (TRU03) was disconnected from one of the servers (server 1, *blue*); Pattern C: one bed unit (TRU02) was disconnected from all three servers

(combined, 99.88 %). Using server 2 as the principle system, additional support was required from the additional servers up to 4.17 % of the total potential collection time.

Discussion

This paper describes the development, testing, and implementation of a triple-redundant, continuous data collection system capable of reliably handling multiple streams of incoming physiologic patient data in a manner that also permits storage and retrieval for quality assurance and a range of clinical research purposes. For 14 years (2000–2013) prior to initiating the system described here, we used a single BedMaster® server as our data acquisition platform and as a critical component that converted signals from multiple bedside patient monitors and stored these data digitally. With this single-server system, continuous data collection rates varied from 50 % to 90 %. In recent years, as our research group has explored these data in increasingly sophisticated ways [4–7, 20, 21], we have become increasingly concerned about the effects of lost data on the sufficiency and unbiasness of study case sampling. The aims of the project described here were to improve overall collection rates, identify causes of data loss, and establish an early warning system that would significantly decrease the lengths and occurrences of gaps in data collection. We believe that the data shown here demonstrate that a triple redundant system is both workable and necessary to fully accomplish our stated aims.

Only the triple-redundant system cannot solve all the issues in a complex and unstable data collection environment, as we can observe from the three servers' performance during the Pre-MoMs months. With the MoMs system, the triple-redundant system could be more robust to system failures with near 100 % collection rate (Table 1). Although a single "backbone" server does most of the collection in a system of the size and complexity of ours and the two additional servers contribute relatively little overall in-fill data, we were interested to see the improvement in total collection achieved by all three servers when they were participating in the post-MoMs system, compared to their relatively tepid performance when isolated. This improved performance was demonstrable for both "up" time, time available for collection, and actual data collection. Using the early notification enabled by the MoMs, data collections are mainly from the principle server, which decreases the overhead associated with switching between servers, but the triple modular redundant design minimized both down time and lost collection time.

We identified a number of reasons for sub-optimal performance by unitary server systems. The most common reason for short gaps in data collection appeared to be the delays inherent in restarting and re-configuring the BedMaster® server after a system upgrade or reboot. The BedMaster® software requires a substantial amount of time to configure

Table 1 Monthly average percentage collection time for each individual server during the developmental phase (Pre-MoMs), and during the deployment phase, (post-MoMs, individual and triple redundant systems), including the average contribution from the auxiliary servers (server 1 and 3) to the primary server (BM2)

	Server 1 collected	Server 2 collected	Server 3 collected	Server 3 contributed	Server 1 contributed	Combined
Pre-MoMs	40.5 %	27.8 %	36.3 %	25.4 %	26.0 %	79.1 %
Post-MoMs	95.4 %	95.5 %	87.1 %	4.2 %	0.2 %	99.9 %

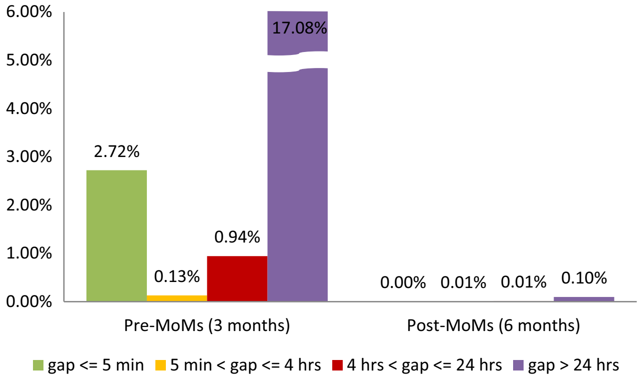


Fig. 4 Pre-MOMs (Feb2013-Apr2013) and post-MOMs (Aug2013-Jan. 2014) BM123 joint collection gaps of different duration categories

each bed for collection. Generally, setting up a single bed takes five steps that take about 10–20 s for an operator familiar with the software [17]. Restarting our entire 94-bed system may up to 30 min, during which time we are unable to capture complete data from all beds.

Data collection may also fail from the bedside. Although we use the BedMaster client software to acquire the latest status of data collection for each bed/monitor unit, this system is insufficiently powerful to formulate an overall picture for all deployed devices nor to aggregate diagnostic information usefully for diagnosis. Beside data collection failure was the second most common source of collection gaps and a frequent cause of extended delays in identification of and response to down time. Additional sources of beside collection failures fell into four general categories: hardware failure, human operator issues, routine servicing of monitors (which includes the need for user reactivation for collection to be resumed) and network failure (servers, bedside devices, and networks are variously located through the trauma center floors and structures). Being able to pinpoint the likely source of collection failure was a particularly gratifying outcome of the work described here.

During the pre-MoMs deployment time, we adopted weekly manual checking to keep the data collection system alive. However, due to the intermittent nature of those component failures, the missing collection gaps still ranged from hours to up to a week days. Configuration of a scalable, user-friendly, real-time dashboard and early warning system for physiologic data collection status contributed directly to the dramatic decrease in gap times and has potential for implementation across the hospital enterprise. Ideally, such systems should report component failure in real-time, provide simple information for diagnosis, and present the pattern of the missing collection, e.g. independent bedside device failure, or batch data server failure, or software failure from the BedMaster server.

An additional potential use for the MoMs viewer is tracking physiologic data from rare events such as that from ICP monitoring systems. An example currently underway in our system is the at-a-glance capability of identifying bed systems that include patients undergoing ICP monitoring so that clinicians involved in a currently ongoing study are alerted to routine needs for blood sampling in these patients. Previously, researchers could have accessed this information only by clicking through each bed tab in BedMaster Client and selecting ICP for viewing, a process that took a not-inconsiderable period of time. With the MoMs, we can enable novel monitoring variables as required and display them in each cell, which increases the awareness of important clinical events and saves manual resources.

The MoMs viewer runs with reasonable robustness and low cost. The server has been deployed on a regular desktop PC with 16 GB memory and Intel® core i5 1.90 GHz. During its stress test with ten simultaneous data output requests and three data servers input, The viewer related service programs consumed less than 1 % CPU and memory resources in average, reported by the system task manager program. This means the MoMs could be deployed on other less expensive computing devices, such as Raspberry Pi under $50.

The MoMs system is highly scalable because of its highly parameterized configuration. The key variables, such as bed units names, locations and numbers, are stored in JSON (Javascript Object Notation) arrays. Visual diagnostic styles are defined in standard CSS (Cascading Style Sheets) files. Clearly separated execution code, parameter configuration and style definition allow users to flexibly add new units or changing the viewer's looking. Interested readers could find example *config* files from our Github repository. However, the MoMs system scalability may be limited by its current

Table 2 Possible system failure reasons and indications from the MoMs viewer

	Failure type	MoMs indicator
BedMaster software	1. Individual bed unit configuration error	Random cells in yellow/red
	2. BedMaster database error	A block of cells in yellow / red; BedMaster server is online
	3. BedMaster service down	A block of cells in yellow/red; BedMaster service stopped
BedMaster hardware	1. BedMaster server down	A block of cells in yellow/red; BedMaster server is offline
Network	1. BedMaster server connection failure	Random cells in yellow/red

visualization style. We hope all bed units information could be displayed within one screen without scrolling for convenient at-a-glance view. Using an equal sized cell (Fig. 2) to represent each bed unit determines that the screen size limit will be reached when the total number of monitored beds grows. The R Adams Cowley Shock Trauma Center has about 113 beds, which can be fully displayed on a regular monitor or tablet screen. The University of Maryland Medical Center has about 757 beds, and the Johns Hopkins hospital has about 1000 beds. It requires more creative visualization techniques to present 10 times more information on one screen. One possible solution is that only bed units with abnormal data collection status will be displayed at different sizes, based on their urgent levels.

Conclusion

Design and implementation of a triple-redundant patient monitor data collection system with at-a-glance real-time display improved the reliability of high fidelity physiologic data collection from 80 % to essentially 100 %. Supported by an efficient back-end data-streaming processing routine and a highly configurable information displaying system, we were able to extract key information from massive data sources and provide instant identification of data collection status, including identification of critical component failures. Essentially complete, real-time collection of massive quantities of an array of physiologic data permits future study design with greatly enhanced confidence in the validity and reproducibility of our results. In future work, we intend to enhance the system information notification modules to transmit system alerts directly to relevant professional staff for system diagnosis or critical medical information updates. We also plan to apply more data aggregation and visualization techniques to enhance access to longer durations of past data, so that the trajectory of system performance or timeseries of important clinical data can be efficiently viewed in real-time.

Compliance with Ethical Standards

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Conflict of Interest The authors declare that they have no conflict of interest.

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