

## Sparsely Sampling Vital Sign Data Limits the Accuracy of Patient State Estimation

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**Background:** Critically ill children exhibit dynamic changes in their clinical state necessitating ongoing evaluation and rapid decision making. Typically, physiologic signals are measured continuously in the critical care unit, but only recorded intermittently in the health record. This low resolution data capture may not accurately reflect the variability of signals or the patient's clinical state, thus limiting accuracy of any derived models. We aimed to characterize how increasing temporal window size (duration) of observation from seconds to hours changes variability.

**Methods:** In this observational study, analysis was performed on prospectively acquired signals (04/01/13-09/30/15) from patients  $\leq 18$  years of age, admitted to the CCU at the Hospital for Sick Children (Toronto). We selected 7 large diagnostic/surgical groups (total  $n=747$ ), in order to allow us to additionally explore the effect of diagnosis/surgery on variance. The physiologic signals evaluated were heart rate (HR) (as beats per minute, derived from electrocardiogram lead recordings) and systolic blood pressure (sBP) (using an arterial line), captured from admission for up to 72 hours. Physiologic data streaming through the Intellivue MP70 bedside monitor (Philips, Amsterdam, Netherlands, software version J.10.50) were captured via an HL7 feed at 5 second increments using the T3 risk monitoring system (Etiometry, Boston, Massachusetts, USA). Standard deviation (SD), a variability measure, was generated as a function of time, using an overlapping sliding window method (window sizes ranging from 10 seconds to 4 hours). A second related variability measure was derived from absolute differences (AD), to specifically explore the accuracy of intermittent sampling in estimating the patient's state in between samples. For each sliding window, the ADs between all values within the window and the first value in that specific window was calculated (distance).

**Results:** In Figure 1A and 1B, we demonstrate at the patient level (using 5 example patients who underwent an arterial switch operation), that the probability of a larger SD and larger ADs for HR, increases with increased time window size when using 4 different window sizes (1 minute, 10 minutes, 1 hour, and 4 hours) for each patient. There were also significant differences in the magnitude of the variance for all time scales between patients within a diagnostic group and between different groups ( $p<0.0001$ ). The window size (seconds) plotted against the mean of the SD (averaged for all patients within a group), and plotted against the median AD, for both HR and sBP is shown in Figure 1C and 1D, respectively. As the window size increases, there is an increase in the mean of the SD and the median AD. We examined the effect of age, by plotting age (years) against SD for both HR and sBP for a 1-hour window size, in all groups (Figure 1E and 1F, respectively). The correlation between patient age and SD of HR, and patient age and SD of sBP was 0.216 (95% CI 0.113-0.315) and 0.33 (95% CI -0.394--0.263) respectively.

**Conclusion:** In complex varying physiologic signals, there is a strong interaction between window size and signal variance. Signal variability increases as the time window of sampling increases from seconds to minutes to hours, at both the individual patient level and group level. In addition, variance is dependent on both admission diagnosis and patient age. Thus, the window size used is crucial when estimating patient state. This supports the case for higher resolution data collection to capture and understand the evolving patient state, and must be taken into consideration when this data is included in machine learning models which guide patient assessment and intervention.

**Figure 1:** **1A**-Distributions of SDs of HR for 5 patients using 4 different time-window sizes. **1B**-Same for ADs. **1C**-Left panel demonstrates the grand mean of the SD of HR, averaged over all patients within each group for each time window size. Right panel demonstrates the same for AD. **1D**-Left panel demonstrates the grand mean of the SD for sBP, averaged over all patients within each group for each time window size. Right panel demonstrates same for the average median AD. **1E**-Average SD of HR for each patient as a function of the patient's age, by group. Calculated for a 1-hour window-size. **1F**-Same for sBP.

