Patient and Room Activity Video Summary (PRAVS) in the ICU: Rapidly Interpretable, ML-Generated Clinical Video Summaries of the Overnight Period

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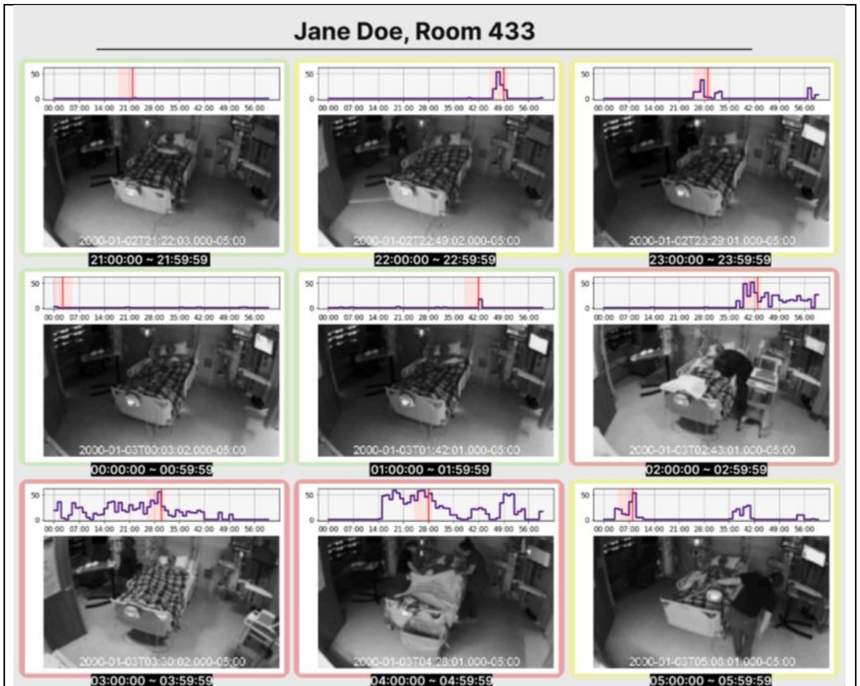
Clinical perspective: Always-on patient activity and room monitoring has the potential to improve patient care, particularly in the overnight period when staffing is often limited and hospital resources do not run at full capacity. Nighttime video actigraphy can help clinicians better characterize patient rest, sleep, delirium and agitation. Both a lack of monitoring and communication about overnight events can leave clinicians with limited information when making decisions about patient care. For example, in the intensive care units (ICUs) patients are often treated with sedative medications overnight for agitation. A clinician may review an overnight video summary and make different decisions about whether to re-sedate a critically ill patient. Video enhanced and processed by ML algorithms is potentially important, as it can help clinicians quickly contextualize changes in patient vital signs, medications and even care plans while augmenting clinical decision making. Here we utilize machine learning to identify the most (max) and least (min) active 5-minute intervals of patient monitoring for each hour in the 9-hour overnight period (9pm to 6am). We took inspiration from vital signs, which are often reported in min/max ranges. We developed a prototype called "Patient and Room Activity Video Summary," (PRAVS) which is presented here. This prototype demonstrates a ML-generated application of always-on video monitoring for clinical use. Our design goal is rapid interpretation within one minute during morning rounds.



Prototype user interface for reviewing the busiest and least-busy 5-minute intervals for each overnight hour. The top of each hourly panel shows the by-minute bedside activity. The bottom of each panel is a looping video of that 5-minute interval played back in 10 seconds (30x speed). The border color of each panel indicates the relative busyness of that hour compared to all 9 overnight hours. Red indicates the 3 most busy; yellow, the 3 middle busy; and green, the 3 least busy. As a matter of routine, all video is blurred before viewing to eliminate visually-identifiable PHI. Additionally, we manually obscured sensitive moments for presentation here. [Max Video Demo] [Min Video Demo].

Study enrollment and machine learning/computer vision: After consent, we deployed a computer vision cart for each enrolled patient. Video data (color and night vision) were streamed to an encrypted hard drive. We ultimately enrolled 22 critically ill patients admitted to the Duke University Hospital Medical Intensive Care Unit (MICU) from 11/2020 to 7/2021 totaling 2155 hours (116 days) of video. This study was approved by the Duke University Hospital IRB. Second-by-second machine learning algorithms generated binary motion counts that were summed by-minute to generate our key motion metric: counts per minute (CPM). This metric can be tuned to identify all bedside activity from patients, staff, and visitors; or can be tuned to focus on patient activity only. Here, we are focused on all bedside activity. Scene intelligence from ML-based object and people detectors provided room environment information. These data streams along with de-identified (blurred) video data were used to generate the prototype graphical and visual summaries of hospital room activity demonstrated here. Please note that the analyses presented here are proprietary.

Initial Interpretation and Ongoing Work: Our initial impression is that the video summaries can give a quick impression if 1) there were barriers to sleep opportunities overnight and 2) if it was a subjectively busy night (e.g. most hours had visitors and patient activity). Two of the authors (SP and MAC) separately reviewed overnight summaries from the initial three nights of enrollment for each of three ICU patients. Video was viewed at 5x speed. Qualitative/narrative observations were documented by-hour. After reviewing these observations, we generated an initial quantitative framework for structured reviewing (and potentially labeling) of the videos. The framework includes: patient (any activity, non-purposeful activity, awoken by staff/visitor), staff (max # in room, at bedside, bedside care, procedure), non-staff visitor (max # in room, at bedside), and room environment (lights on, lights turned on, light pollution (screens, hallway, etc.)). Our ongoing work includes developing a rigorous clinical validation framework and developing an interactive user interface for integration into morning rounds. An initial prototype of this UI is shown above.