Intelligent ICU for Autonomous Patient Monitoring Using Pervasive Sensing and Deep Learning

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Background

Every year, more than 5.7 million adults are admitted to intensive care units (ICU) in the United States, costing the health care system more than 67 billion dollars per year[1]. A wealth of information is recorded on each patient in the ICU, including high-resolution physiological signals, various laboratory tests, and detailed medical history in electronic health records (EHR)[2]. Nonetheless, important aspects of patient care, including patient's facial expressions of pain, mobility and functional status are not captured in a continuous and granular manner, and require self-reporting or repetitive observations by ICU nurses[3-7]. This lack of granular and continuous monitoring can prevent timely intervention strategies[8-13].

Objective

In ICU settings, doctors are required to make life-saving decisions while dealing with high level of uncertainty under strict time constraints to synthesize high-volume of complex physiologic and clinical data. On the other hand, assessment of patients' response to therapy and acute illness is mainly based on repetitive nursing assessments, thus limited in frequency and granularity. We propose that artificial intelligence (AI) technology could assist not only in administering repetitive patient assessments in real-time, but also in interpreting and integrating these data sources with EHR data, thus potentially enabling more timely and targeted interventions[14,15]. We examined how pervasive sensing technology and AI can be used for monitoring patients and their environment in the ICU.

Methods

The pervasive sensing system for data acquisition included (1) a high-resolution and wide-field-of-view camera, (2) three wearable accelerometer sensors, (3) light sensor, (4) microphone for capturing sound pressure levels, and (5) a secure local computer. We captured video using a camera with a 90^{o} diagonal field of view with 10X optical zoom for zooming on the patient face. We used three Actigraph GT3X devices on the patient's wrist, arm, and ankle to record patients' activity intensity throughout their enrollment period. To capture the effect of environment disruptions on sleep quality, we recorded light intensity and sound pressure levels in the room throughout the patient's enrollment period using an iPod and a light sensor. EHR data included physiological signals recorded in the ICU via bedside monitors, as well as demographics, admission information, comorbidities, severity scores, pain and CAM-ICU[16] scores, laboratory results, medications, procedure and diagnosis codes, and enteral feeding status. We administered daily questionnaires to assess patients' sleep quality during their enrollment.

We used the Joint Face Detection and Alignment using Multi-Task Cascaded Convolutional Network[17] to detect individuals present in each video frame. 65,000 video frames were annotated by delineating a bounding box surrounding each individual. Next, we performed face recognition using FaceNet[18] algorithm to identify the patient in each video frame. First, we extracted 7 seconds of still images at 15 fps containing the patient face, as training data. Training data were passed through the face detection pipeline. The trained classifier for each patient was tested on 6,400 randomly selected images of the same patient. After detecting and recognizing patient's face, we localized anatomical key-points of joints and limbs using the real-time multi-person 2D pose estimation[19] with part affinity fields. This allowed us to recognize poselets, which describe a particular part of posture under a given viewpoint. The part affinity fields are 2D vector fields that contain information about the location and direction of limbs with respect to body joints. Our pose detection model used Fully Convolutional Neural networks[20] branches and k-nearest neighbor classifier[21] to detect the location of the joints and the association of those body joints as limbs, and then to identify the full posture. To train the model using a balanced dataset, we augmented ICU patient data with scripted data. We considered four main posture classes to be recognized: lying in bed, standing, sitting on bed, and sitting on chair.

For each video frame, facial Action Units (AUs) were obtained using the OpenFace[22] toolbox and used to detect eight facial expressions: pain, happiness, sadness, surprise, anger, fear, disgust, and contempt. Facial expressions were calculated using Facial Action Coding System formulas[23,24]. We also calculated 15 statistical features to summarize the accelerometer data.

Results

We recruited 22 patients in the surgical ICU at a quaternary academic hospital. Delirious patients and non-delirious patients did not significantly differ in baseline characteristics, except for the number of comorbidities. We collected 33,903,380 video frames visibly containing face, 16,123,925 video frames of patient posture, and 3,203,153 of patient facial expressions. We also collected 1,008 hours of accelerometer data, 768 hours of sound pressure level data, 456 hours of light intensity level data, and 1416 hours of physiological data. For training our deep learning models on ground truth labels, we annotated 65,000 video frames containing individual faces, and 75,697 patient posture video frames. Face detection and patient face recognition models achieved Mean Average Precision value of 0.94 and 0.80, respectively. We detected 15 AUs from 3,203,153 video frames. Successful detection was achieved for 2,246,288 out of 3,203,153 video frames (%70.1). All AUs were significantly different between delirious and nondelirious patient groups (p-value<0.01). Delirious patients had suppressed expression for seven out of eight emotions (p-value<0.001, except for anger). Delirious patients exhibited significantly less variation in head poses compared to the non-delirious patients (p-value<0.001). Delirious patients on average had fewer visitor disruptions during the day, but more disruptions during the night.

Our posture recognition model achieved an F1 score of accuracy of 0.94. The individual classification accuracy of recognizing postures was: lying = 94.5%, sitting on chair = 92.9%, and standing = 83.8%. Delirious patients spent significantly more time lying in the bed and sitting on chair compared to non-delirious patients (p-value<0.05 for all four postures). Delirious patients had higher movement activity for wrist during the entire 24-hours cycle, daytime, and nighttime. The 10-hour window with maximum activity intensity showed different levels of activity between the two patient groups. However, activity in the 5-hour window with the lowest activity intensity was not significantly different, possibly due to low activity levels in ICU in general. Delirious patients had a lower number of immobile moments during the day and during the night, hinting at their restlessness and lower sleep quality. The sound pressure levels and light intensity levels for delirious patients' rooms during the night were on average higher than those of non-delirious patients' rooms. Average nighttime sound pressure levels and light intensity levels were significantly different between the delirious and non-delirious patients (p-value<0.05). Delirious patients reported a lower overall ability to fall asleep compared to non-delirious patients, and they were more likely to find the lighting to be disruptive during the night (p-value= 0.01, p-value=0.04, respectively).

Discussion

We showed the feasibility of pervasive monitoring of patients in the ICU. This is the first study to develop an autonomous and comprehensive system for patient monitoring in the ICU. We performed face detection, patient face recognition, facial action unit detection, head pose detection, facial expression recognition, posture recognition, extremity movement analysis, sound pressure level detection, light intensity level detection, and visitation frequency detection, in the ICU. As an example, we evaluated our system for characterization of patient and ambient factors relevant to delirium syndrome[25-27]. We found that facial expressions, functional status entailing extremity movement and postures, and environmental factors including the visitation frequency, light and sound pressure levels at night were significantly different between the delirious and non-delirious patients.

Conclusion

To the best of our knowledge, this is the first study to continuously assess critically ill patients' facial expressions and functional aspects along with environmental factors such as noise and light. Our collected data hint at several interesting observations, including more significant disruption of the circadian rhythm of physical activity in delirious patients, as confirmed by other studies[28-30]. We expect future similar systems can assist in administering repetitive patient assessments in real-time, thus potentially enabling more accurate prediction and detection of negative events, and more timely interventions, reducing nursing workload, and opening new avenues for characterizing critical care conditions on a much more granular level.

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