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Enhancing Safety of Artificially Ventilated Patients Using Ambient Process Analysis

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Abstract. In this paper, we present an approach for enhancing the safety of artificially ventilated patients using ambient process analysis. We propose to use an analysis system consisting of low-cost ambient sensors such as power sensor, RGB-D sensor, passage detector, and matrix infrared temperature sensor to reduce risks for artificially ventilated patients in both home and clinical environments. We describe the system concept and our implementation and show how the system can contribute to patient safety.

Keywords. Ambient Process Analysis, Artificial Ventilation, Home Mechanical Ventilation, Patient Safety, Ambient Intelligence

Introduction

It is unclear how many people in Europe are artificially ventilated, but Lloyd-Owen et al. reported in a study carried out from 2001 to 2002 that the prevalence of home mechanical ventilation (HMV) is 6.6 per 100,000 people [1]. Applying this figure to the estimated 512 million of the European Union, around 34,000 people were artificially ventilated at home in the EU at the time of the study. However, this number is subject to uncertainties, as the prevalence for the individual countries varies [1]. Nevertheless, it is evident that a considerable number of people are artificially ventilated at home. It requires ventilators (artificial lungs), monitoring devices, nursing and respiratory equipment, and 24/7 intensive care staff to enable artificial ventilation at home.

In such a complex conglomeration of techniques, methods (e.g., for intensive care) and humans, critical situations can arise that pose a threat to the safety of the patient. For example, there are situations when the respirators are disabled, or its alarms are muted or deactivated. Although the nursing staff is (theoretically) 24/7 available, such situation can end lethally for the patient [2].

In this paper, we present a concept for an Ambient Process Analyzer (APA). The APA uses the information provided by ambient sensors such as RGB-D (RGB + Depth) motion sensors, infrared temperature sensors, passage detectors, and power sensors 1.) to identify possible critical situations within health care situations and 2.) to generate

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context-sensitive alarms. This improves patient safety with another safety guard and relieve caregivers by avoiding unnecessary false alarms (alarm fatigue).

1. Related Work

The safety of HMV patients can be improved through different approaches ranging from enhancing nursing staff team culture [3] over hygiene standards to observation technologies. There are some approaches to improve patient safety in clinical intensive care units (ICU) in general [4], but little can be found regarding intensive care at home. Orlikowski et al. [5] have evaluated the monitoring of ventilation efficiency with ventilator-integrated End-Tidal CO_2 sensors. Their approach requires a close-to-body sensor, whereas our approach is based on ambient sensors.

Ambient sensors, on the other hand, have been widely adopted for Ambient Assisted Living (AAL) to enhance the safety of elderly at home [6], e.g., fall detection concepts [7]. Wiede et al. for example summarize the use of RGB cameras to derive vital parameters of patients at home [8].

2. Concept

2.1. Enhancing Safety of Artificially Ventilated Patients

The joint research project MeSiB aims to increase the quality of life and the safety of ventilated patients, especially in home environments. This will be realized through the specific use of technologies for monitoring and for generating context-sensitive alerts for the nursing staff. The APA, which will be presented in detail in the next subsection, is the central software component that uses data from a variety of ambient sensors to provide context-sensitive monitoring of critical processes and conditions within artificial ventilation. It will work in close conjunction with a Rules Engine that decides the warning and alert actions based on the state data the APA provides.

2.2. Ambient Process Analyzer

The APA is a multisensory system consisting of ambient sensors (hardware), sensor fusion (software), and state derivation units (software). The APA's objective is: determine the state of the patient, of the caregiver/healthcare personnel, and of the life-preserving devices, i.e., the ventilation machine.

The basic structure of the APA is outlined in Figure 1. The input (1) of the APA is sensor data from an RGB-D (RGB + Depth) sensor, a power sensor, an infrared array temperature sensor, and passage detectors. The RGB-D and the power sensor are input to Sensor Fusion Unit A (SFU-A, (2)), which derives the patient's state (e.g., vital signs or location). The RGB-D is also an input for Sensor Fusion Unit B (SFU-B, (3)), together with the infrared array temperature sensor and the passage detection sensor.

Both SFUs derive the patient's and the caregivers' state (the latter based on presence and activity detection) and transmits the result states via HL7 Version 2 ORU to a further deciding Rules Engine (4), which is located on an independent device. With data from the power sensor alone, the state of ventilation machine could be derived, e.g., ventilating, standby or offline.

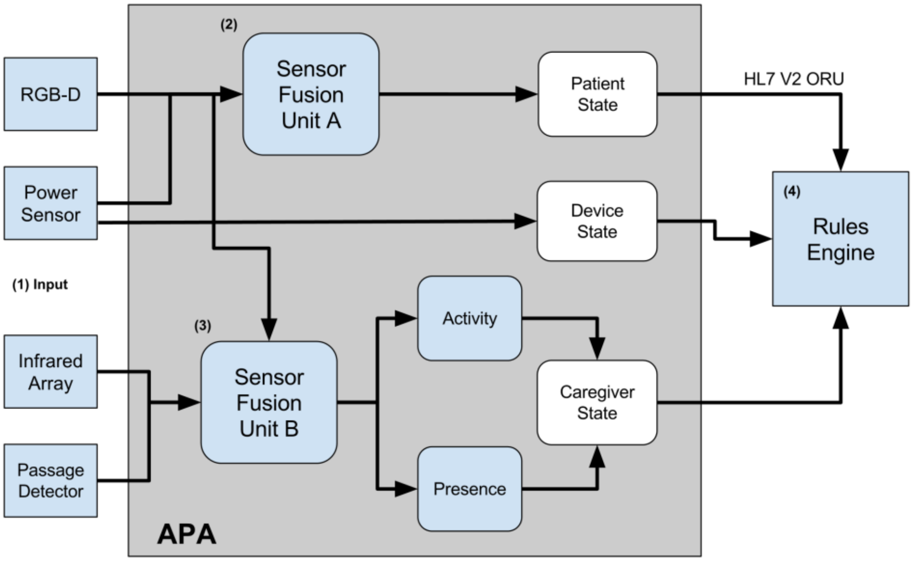

Figure 1. Structure of the Ambient Process Analyzer (APA)

3. Implementation

Our APA-implementation incorporates four different sensor types (see section before), the actual sensor hardware in our implementation are Microsoft Kinect (RGB-D), Panasonic Grid-Eye (Infrared Temperature Sensor), ELV HmIP-SPDR (Passage Detector) and a custom build power sensor.

3.1. Algorithms for Patient State Detection

Deriving the status of the patient is not trivial. Artificially ventilated patients are usually immobile or minimal mobile in bed, making it difficult for ambient sensors to capture reliable data. Nevertheless, two statements that could be made by external sensors are of interest: first, reliable ventilation of the patient is of vital interest. If the ribcage is visible to the RGB-D sensor, our approach will try to use the depth image of the sensor to detect the raising and lowering of the rib cage, i.e., breathing. Although the reliability of such detection is likely to be low, the information from that sensor may improve the detection of the other sensors so that that overall a reliable statement can be made about the state of the patient's ventilation.

The second aspect is the monitoring of the patient's situation in the hospital bed. Bedridden patients must be regularly moved, for pressure ulcer prophylaxis and atelectasis and pneumonia prophylaxis. It is possible to detect the position of the patient in bed by the folds of the duvet to a certain extent [9], [10]. We want to expand on this approach and thus recognize how the patient has been relocated. A downstream system can use this information to generate information or warnings for nursing staff.

3.2. Presence and Activity Detection

The Rules Engine requires the number of persons that are present in the room of the patient, because some situations, e.g., a break in the respiration flow, may be uncritical if caretakers are present but may be critical if the patient is alone. Therefore, we detect the number of persons present in addition to the patient. For a safety system, it is necessary to obtain an excellent detection rate. However, as literature shows [11], a precise presence detection can only be obtained by cameras, which cannot be used in some countries because of their poor acceptance and privacy issues. Thus, we propose a system with two recently introduced sensors: The Panasonic Grid-Eye sensor and the passage detector (HmIP-SPDR) by ELV.

The Grid-Eye sensor is an infrared temperature array sensor. This sensor provides an 8x8 matrix of temperature values and covers an angle of about 60°. This sensor is placed above the patient's bed with the aim to detect the number of persons next to the patient. We will use machine learning techniques to train an algorithm, which detects the number of persons based on the sensor data. The passage detector is equipped with two sensing elements that allow the system to detect the direction of persons passing the sensor. The output of the presented presence detection sensors will be sent to the rule engine using the HL7 V2 ORU message type.

The Kinect sensor also contributes to the activity detection of the caregiver. At first, we segment the motion data of the Kinect using an unsupervised motion segmentation algorithm [12] before a classification algorithm is used to detect activities.

3.3. Power Supply Monitoring

A report documented in the Critical Incident Reporting System (CIRS) shows that unintended status changes of the respiratory device may cause the death of the patient [2]. In the reported case, the respirator was unintentionally switched to standby mode. A disconnection from the power supply is valuable information for the safety rule engine as well. Although modern respiratory devices use batteries to allow the devices for hours to function without an active power supply, still, a disconnection of the respiratory device can be critical if the device is not well charged.

In our approach, we propose to monitor the power usage of a respiratory device. This could provide additional certainty about the device state (e.g. "active" or "stand-by") and be used for the identification of the disconnection of the power supply.

We will use a power sensor plug to detect the electricity usage of the respirator. In a previous work [13], a charger showed significant differences in phase related current signal features obtained from a smart meter measurement. We assume that this finding could enhance the detection of the ventilation machine's state and the state of the power supply because respiratory devices also have a charging element.

4. Conclusion

We presented the concept of an Ambient Process Analyzer (APA), which uses ambient sensors, data fusion, and appropriate algorithms to provide a decision support system with patient-, nurse-, and ventilator-states. The APA transmits its information in HL7 OBX messages to the higher-level rule machine. With the combination of a Rules Engine and the APA, context-sensitive information and alarm messages can be generated for the carer (audio or visual) or subordinate emergency physicians/services (emergency call). The APA thus contributes to the improvement of patient safety and the reduction of the mental load (to avoid alarm fatigue) for the caregiver by intelligent and context-dependent notifications. The complete system will be evaluated in both the clinical setting on a weaning station and an HMV setting at home.

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