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Utilizing Intensive Care Alarms for Machine Learning

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Abstract. Alarms help to detect medical conditions in intensive care units and improve patient safety. However, up to 99% of alarms are non-actionable, i.e. alarm that did not trigger a medical intervention in a defined time frame. Reducing their amount through machine learning (ML) is hypothesized to be a promising approach to improve patient monitoring and alarm management. This retrospective study presents the technical and medical pre-processing steps to annotate alarms into actionable and non-actionable, creating a basis for ML applications.

Keywords. Alarm management, patient monitoring, machine learning

1. Introduction

Alarms are essential in a medical care setting as patient safety in intensive care units (ICU) relies on effective alarm systems and management [1]. Up to 99 % of alarms are non-actionable [2], meaning no medical intervention is required. So far, it is not possible to identify a medical intervention in a retrospective analysis of our hospital's alarm data nor do other publicly available databases contain such information. In this retrospective study, we aim to describe the requirements for a semi-automated annotation of alarm logs, enabling the deployment of machine learning (ML) algorithms at a later stage.

2. Methods

Through medical pre-processing, we identified clinical use cases, alarm types, patient health data related to interventions, and defined an annotation rule set based on conceptual mappings. During technical pre-processing, we extracted alarm logs from monitors and patient health data from the patient data management system, and explored database schema. We identified alarm start, pause and end times, and mechanisms to remap alarm log entries to patients' data. To execute the alarm annotation, we translated medical knowledge into executable scripts. IRB approval was obtained.[2]

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3. Results

For the timeframe March 2019 to October 2021, the alarm logs include 37,325 patients with 43,603 ICU stays. Clinical use cases and respective annotation rules are iterated and validated by focus groups with medical experts. “Low oxygen saturation” was chosen as the first use case, with an annotation rule set including numerical (e.g. oxygen saturation) and categorical (e.g. ventilation devices and modes) values. We applied the Medical Information Mart for Intensive Care (MIMIC) IV database schema [3,4] for patient health data with additional tables for alarm data. These include 40,942,722 alarm log entries with 15,551,660 alarm starts, 971,598 alarm pauses, and 15,555,489 alarm ends. Alarm starts are the reference point for annotations. The conceptual mappings are translated into a set of lookup tables. Python 3.7.6 and execute SQL statements automate the annotation and investigate the respective patient data points before and after an alarm.

4. Discussion

A database that combines patient health data and alarm data was built and a rule set for alarm annotation was defined. Alarm logs cannot be annotated in isolation, but rather in conjunction with other patient health data. The amount of medical and technical pre-processing presents a strong inhibitor to utilize ML for improved alarm management. Only a diverse team of medical and technical experts can give meaning to otherwise unlabeled, unstructured alarm data [5]. Manual annotations are cumbersome and error-prone [6]. Therefore, iterative implementation phases with quality insurance checks from clinicians can pave the way towards semi-automated alarm annotation.

5. Conclusion

A retrospective annotation of alarm data into actionable and non-actionable alarms could provide the basis for ML applications, pioneering a more intelligent, technology-aided or -driven alarm management.

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