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Estimation and Monitoring of Operating Room Utilization by a Distributed Streaming and Analytics Architecture Deployed at Heidelberg University Hospital's Medical Data Integration Center

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Abstract

Operating rooms are a major cost factor in a hospital's budget. Therefore, there is a need for process optimization related to the operating rooms (OR). However, the collection of key figures for process optimization is often done manually by medical staff. This can be erroneous, inaccurate, time consuming, and incomplete. Automated, data-driven approaches are intended to address these problems and help to get the most precise picture possible of what is happening within the OR. At Heidelberg University Hospital (UKHD), a distributed AI based streaming analytics architecture was set up and integrated into the Medical Data Integration Center (MeDIC). This architecture can process, store, and visualize heterogeneous data from different sources. Data from medical devices and the video stream of the wall mounted cameras of four integrated operating rooms are ingested into our system. Aggregated and analyzed in real-time computed key figures including OR state and utilization numbers are visualized in a dashboard for monitoring and decision support. Because of high data protection hurdles the proposed system, especially the video analytics, was trained and tested with statists and did not run during real procedures. Studies to evaluate and test the system during live surgeries are planned.

Keywords:

Operating Room Information Systems, Artificial Intelligence, Data Management, MeDIC, Interoperability

Introduction

It is in the interest of every clinic to make processes more efficient to save time and money. More precise planning and optimized processes should contribute to better patient care and relieve the staff. Determining and optimizing the occupancy rate of an operating room as one of the biggest cost drivers plays a decisive role [1]. Therefore, it is necessary to find a way to measure and analyze the duration of each individual intervention and how to optimize it. However, every procedure is a complex task influenced by each involved individual and several external factors [1]. Emergency add-ons, cancellations and delays can have a negative effect on the clinical processes [2]. There are OR management software solutions which tackle those issues, but in most cases the user has to manually enter important key figures such as the surgeon's arrival in the OR, cut-suture time, or the patient duration time. This is error prone as it is an additional work step that must be carried out during the OR [3]. Hence data is often entered afterwards, according to the procedure, it can be incomplete or only a rough estimation. These inaccuracies can affect planning and optimization in the future [4]. Furthermore, nowadays it is still often the case that the status of the ongoing OR is not known. OR coordinators, which are in charge to plan the subsequent procedure, including to trigger tasks like preparing the next patient, must walk through the OR aisle to investigate the current state.

The key to a more precise and reliable determination of the relevant OR times and the total workload is to find a solution to determine the most comprehensive possible picture of what is happening within the black box OR based on automated aggregation and analytics of heterogenous data sources [2]. On the one hand, such a system can help monitoring the status within an OR in real time and enables a quick reaction to unplanned incidents [4]. This gives the OR coordinator the opportunity to optimize the processes at short notice by rescheduling follow-up operations to keep delays as short as possible. On the other hand, the recording and retrospective analysis of this data can be used to automatically calculate key figures such as turnover times, total durations and thus improve clinical planning processes [5]. It is important to collect as much information as possible regarding the interventions that are available, e.g., medical device data [6], data from external installed sensors [2], video data, vital sign data during a surgery or data from clinical information systems. However external sensors often require an additional infrastructure which must be build up in a restricted clinical environment. The usage of existing sources avoids awkward installation and management processes.

In order to manage large amounts of heterogenous data a scalable, fail-safe, and expandable IT architecture is necessary. At UKHD the MeDIC [7] meets these requirements. Additionally, it must be able to process real-time information like OR video streams and high frequency medical device data. It should be capable of analyzing and visualizing retrospective data, always under the premise of data protection and security.

Methods

The PART research project (Predictive Analytics of Robustness Testing) aims to establish a monitoring system for networked medical devices. A data pipeline which is designed to store, analyze, and visualize device data from different manufacturers in real-time was set up [6]. The focus of this work was on profitability analysis and system monitoring of medical devices. The presented work takes up the idea of PART and expands it from the monitoring system for networked medical devices to a monitoring and utilization system of four ORs at the UKHD based on medical device and video data analytics deployed in the MeDIC.

MeDIC IT Architecture

The MeDIC at UKHD provides a multipurpose medical data integration environment to support clinical care as well as biomedical research with semantically enriched, high quality clinical routine data. The MeDIC brings together fragmented data residing at various data sources spread over the hospital's IT landscape. Thus, a holistic data view on patients, resources and processes can be made available. The data integration is based upon utilization of internationally established, open interoperability standards like HL7v2, HL7 FHIR, DICOM and openEHR. So far, the MeDIC connects to around ten clinical primary systems including amongst others hospital information system, laboratory information system, intensive care documentation, cardiology-specific sub-systems, and clinical cancer registry. The MeDIC IT architecture is structured in several layers as Figure 1 depicts.

The following steps were conceptualized, planned, and technically implemented using an agile approach. The connection of four operating rooms of the surgical clinic to PART. Design and implementation of a data protection compliant video analytics

Figure 1 – Medical Data Integration Center (MeDIC) Infrastructure. The integrated PART components depicted in red

pipeline. A dashboard for visualization and the integration of the PART components into the MeDIC.

Results

To be able to process and store huge amounts of heterogeneous data the PART pipeline architecture with its processing components was integrated into the MeDIC IT infrastructure. The presented system collects the data of all available data sensors from four operating rooms, processes them and calculates key figures regarding the state and the utilization of the ORs.

PART MeDIC Integration

Figure 1 shows the components of the PART pipeline architecture integrated into the layered MeDIC infrastructure in red. Subsequently, each component of PART within the associated layer is described in detail.

Source Layer

Four integrated ORs from the surgical clinic were added to the source layer as primary systems. Wall mounted IP-based fisheye cameras and the medical devices located in each room serve as data sources.

Video Camera Data

- High data protection requirements were considered when designing the video stream IT architecture. The images from the cameras are encrypted and transmitted for further processing to the Data & Analytics Layer through the Integration Layer.

Medical Device Data

- The medical devices including OR-lights and insufflators are connected to a so called Datalogger computer located within the OR. This machine from the project partner KARL STORZ GmbH & Co. KG. collects the device data and sends it to the Integration Layer through an Apache Kafka producer [8].

Integration Layer

A Kubernetes orchestrated Apache Kafka cluster consisting of 3 nodes serves as a distribution point for the device data. The data from the Kafka producers running on the Dataloggers is received and made available for consumption.

Data & Analytics Layer

Four components of PART extend this layer. First, Elasticsearch (ES) [9] was deployed in the MeDIC as the main data store of PART running as Kubernetes orchestrated cluster. The Analytics section was newly added to the MeDIC infrastructure with the PART integration including three components. The Medical Device Data analytics component and for the video data two consecutive components. The AI Video Evaluation and the Video Feature Analytics components managed as Docker containers, see Figure 1.

Medical Device Data Analytics

This component is implemented as an Apache Flink [10] consumer. The medical device data streams from the Kafka Broker running in the Integration Layer are merged to one combined OR device data stream. This combined stream is processed in real-time to calculate the following room utilization figures:

- the total number of times the room is used
- the average time of one usage
- the average usage time per day
- the number of times it was used per day
- the utilization as the ratio of hours used and total number of hours a day

AI Video Evaluation

High data protection hurdles severely restrict the use of live images from the surgery rooms. Therefore, the system requirements included automatic evaluation of the data in real time, only revealing relevant information to the end user in compliance with data protection regulations. In cooperation with the Fraunhofer Institute of Optronics, System Technologies and Image Exploitation (ISOB), a video analysis software based on artificial intelligence (AI) was adapted and extended according to our requirements.

1

2

3

Figure 2 – OR State computation based on AI driven video stream analytics and complex event processing. Each row includes two images. On the left the video stream and the detected object class of the AI is shown by a white rectangle. On the right the dashboard shows the resulting state of the OR and the computed utilization figures. State 1: The patient (circle lights up red) and one medical professional (circle lights up red proportionally) are detected. State 2: Two medical professionals are currently in the OR. State 3: The room is empty and shown as inactive (blue square in the upper left corner). Note, as soon as the patient or the last medical professional left the length of stay is computed and depicted in the dashboard.

With the aim of displaying the status within the operating rooms the AI software was trained on the object class "patient" and "medical personnel" in several measurement campaigns carried out at the UKHD. The software, based on a deep learning approach can extract the following features from the video stream in real time:

- Number of medical personnel
- Patient in the operating room

The video images from the cameras are not saved at any time and cannot be viewed by third parties. Fully automated processing takes place within the secure IT infrastructure of the UKHD. As soon as one of the features is detected, an event is sent as a JSON formatted text message including timestamp and feature to the Video Feature Analytics component for further processing and visualization. Note, the AI Video Evaluation component transforms the video stream automatically in an event-based feature stream from which one can no longer infer to a specific person in the room. The output of this component is sent to the Kafka Broker for further consumption and processing by the Video Feature Analytics component.

Video Feature Analytics

To compute OR utilization figures the feature stream from the preceding AI Video Evaluation is processed a second time in the Video Feature Analytics component. An Apache Flink Consumer either passes through the events to directly show the OR state in the dashboard, e.g., number of medical professionals in the room, or observes the infinite feature stream to extract the following key figures when they occur:

- Patient duration in the OR
    - Elapsed time between entering and leaving the room
- Medical personnel duration in the OR
    - Elapsed time between medical staff is entering and leaving the room
- Turnover Time (patient to patient)
    - Elapsed time between two consecutively "patient entered" events
- OR active / inactive
    - Same as total duration of medical personnel. From the first person entering the room, to the last one leaving it
- Number of interventions
    - Derived from the number of patients entered the OR

Figure 4 – The OR Monitoring & Utilization Dashboard of the surgical clinic at UKHD

If a feature is detected a new event is created and sent for storage to ES.

Service Layer

The results of the Data Analytics layer are visualized in the newly created PART OR Monitoring and Utilization dashboard. This dashboard is created with Kibana [11] the visualization tool of ES, described subsequently.

OR Monitoring & Utilization Dashboard

The overview page of the PART dashboard shows all available ORs of the surgical clinic, see Figure 4. Via a link the user reaches one specific operating room of interest. A rectangle shows whether the room is active (red) or inactive (blue). This state is derived from the current device data flow. Figure 3 shows the start page for room number nine exemplarily. Room utilization numbers and information on the devices located in that room are displayed. The horizontal band highlighted in blue shows the key figures related to OR utilization, computed in the Data Analytics Layer, see Figure 1.

Below this area the user finds links which yield to the monitored devices in this room, OR-light, and insufflator. To the right of this, the start and end time as well as the duration of the last three interventions are tabulated. In the lower area of this page the band with the white background shows real-time information of the devices. When a device is currently in use it is shown here. The real-time state for the same room, calculated based on the Data Analytics Layer is shown in Figure 2. Three situations are depicted. Each described by two pictures in a row:

1. Room is active. The patient and one medical professional are in the room The AI system detects the two objects (white rectangle in the left picture) and in the PART dashboard the status "room active" is indicated by the red square in the top left corner. This information is derived from the extracted feature "OR active/inactive". The information whether the patient and the medical staff are in the room is indicated by the pie charts in the middle section of the page. If the patient is in the room, the color of the circle turns from blue to red as it is shown. For medical staff, the circle is filled up by red depending on the number of people currently in the room. In addition, the number is shown in the center of the circle.

2. Room is active. Two medical professionals are in the room. The Medical circle is filled up by red proportionally. The number of people is shown in the middle of the circle.

3. Room is inactive. In the bottom row of Figure 2 the room is empty. Patient and medical staff has left. Immediately the duration is calculated and shown in the dashboard.

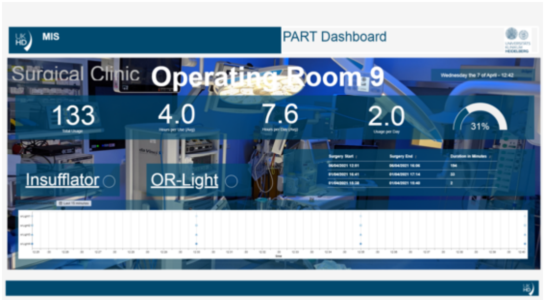

Figure 3 – OR9 Dashboard: Shows key figures according to utilization and live coverage based on the merged and analyzed medical device data stream

The time when the room was entered, and the duration of every stay are displayed for patients and medical staff below the pie chart. Further the patient turnover time is shown. It gets updated when the next patient enters the room.

Discussion

In the presented work a monitoring and utilization system for ORs is proposed. Through processing heterogenous data sources in real-time it is supposed to help improve clinical processes around the operating room.

To improve results, computing more key figures and getting a better insight into the OR and the procedures the connection of more data sources, e.g., endoscopes, light sources, OR-light cameras, and HF devices is necessary.

For testing, comparison and detecting deviations of the automatically computed key-figures against the manually entered ones from the clinical information system the integration into PART is planned. This would give insights how reliable the proposed system is working.

To make predictions and forecasts about how long a procedure is going to be, analytics on large amounts of retrospective heterogenous OR related data and their linkage is necessary. The proposed infrastructure is designed for research on AI based solutions of retrospective data too. Operating teams and nurses could be automatically informed based on those results to prepare for the next surgery, the next patient, respectively. This could shorten waiting times and thus help to optimize the workflow. These experiences can then help to plan and coordinate operations better in the long term.

The AI Video Evaluation system was trained and tested with statists. So far, it did not run during a real procedure due to high data protection hurdles. Here we are working with the greatest possible transparency and clarification to create acceptance for this technology among all involved people. As part of a study, it is planned to evaluate and further test the system during live surgeries. This will bring new findings and results on robustness and reliability of our system and whether it delivers the desired added value.

Conclusions

With the integration of PART into the MeDIC and its extension through new data sources and AI-based analysis the technical foundation was established to monitor the operating rooms at UKHD in an automated, data-driven manner. The OR Monitoring & Utilization Dashboard provides a new service towards clinical process optimization and decision support within the OR and gives users, e.g., the OR-coordinator, a tool at hand that enables live coverage, utilization, and short-term monitoring of four integrated ORs of the surgical clinic.

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