A System for Tracking Patients in the Operating Room - A Pilot Study*

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Abstract

Operating Room (OR) management represents one of the most important processes in healthcare organizations. Inefficient scheduling and inefficient human allocation often negatively affect OR's management processes. This pilot study aims to optimize the management of a generic operating block by automatically collecting data from a real surgical scenario. The final goal of the project will be the development of a new organizational model based on machine learning algorithms. Each patient is tracked and located in real time through an architecture that recognizes a wearable tag with a unique identifier. By exploiting indoor localization techniques, we can collect data about the time required by every step of the patient's management process in operating block. The preliminary results are promising, times automatically recorded are much more precise than those collected by humans and reported in the organization's information system. Moreover, machine learning methods can use historical data collection to predict the surgery time required for each patient according to their specific profile. This approach will make it possible to plan short and long-term strategies while optimizing the available resources. Finally, the integration of the IoT system with ML algorithms could contribute to the optimization of the operating block scheduling and will be the subject of further research.

Keywords

Surgery, Electronic health records (EHR), Prediction model, Operating room (OR), Machine learning, Case prediction

1. Introduction

Operating Rooms are responsible for large amounts of profits and costs [1]. About 60% of all hospitalized patients are treated in the OR [2]. This makes surgical scheduling a key process in the perioperative organization. If cases consistently run longer than expected, OR over-utilization will result in costly overtime pay and staff dissatisfaction. On the other hand, if

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actual case times are shorter than expected, OR under-utilization becomes staff idle time, which can increase costs by up to 60% [3].

Case duration is usually predicted by the surgeon who uses his/her experience to reserve a time slot. Such predictions of case duration have been proven that tend to underestimate case duration by up to 42% of the time and overestimate it by up to 32 % [4].

Another common approach is to use the electronic health record (EHR) to calculate case duration based on historical data. The use of EHR gives better accuracy, but does not take into consideration the patient's anamnestic data.

The main issue with ML methods is providing accurate and noise-absent samples to the model, which is critical when historical data are collected by humans. In light of this, the aim of our research project is to develop an integrated technological-organizational model capable of processing data deriving from ORs to optimize the management and organization of the whole operating block.

To achieve such a result, we have developed an IoT-based multi-agent architecture that is able to collect real data to minimize errors or noise in data in order to maximize ML algorithm performances. The main architecture's goal is developing an optimal scheduler for surgical procedures that leverages Agent-based simulation techniques [5] by integrating clinical/anamnestic information, data from the analysis of surgical timing, and time spent in the Recovery Room (RR) in order to optimize OR management.

2. Literature review

The use of Big Data and machine learning (ML) offers considerable advantages for the collection and evaluation of large amounts of complex health-care data [6].

Many results are available about the excellent capabilities of AI tools in healthcare, such as drug discovery [7], clinical trials [8], and disease diagnosis [9].

The use of AI is not limited to predictions and diagnosis, but it is also gaining increasing attention for healthcare management tasks [10, 11] where agent-based simulations (ABS) describe the system with a high resolution of details as well as modeling scenarios with different levels of available resources or uncertainty, such as: [12, 13] to predict COVID-19 outbreaks with fine-grained details in large scenarios; [14] that models the critical care pathway for cardiothoracic surgery with Discrete event simulation; [15, 16] where ABS techniques are leveraged to build intelligent decision support systems that guide hospital's managers to the reorganization and verification of healthcare business processes.

Agent-based models for healthcare management can also be empowered with Machine Learning, especially for risk estimation, for forecasting healthcare costs, risk of readmission, and hospitalization [17].

Luo et al [18] apply ML models to estimate the risk of cancellation of an operating session, with the negative impact that this entails both in terms of costs and on waiting lists and therefore also translates into delayed access of the patient to surgery.

A novel approach has been presented by Abbou et al. [19]. In this study, the authors used data from EHR from December 2009 to May 2020 for a total of 297,480 interventions of two public hospitals in Israel in this study. They use pre-operative data to predict the duration of the surgery, including patient clinical data, the experience of surgeons, patient nationality, results of analyses carried out before the operation, etc. They compared the predictions between a naïve model and a ML model (Xgboost), with various metrics: root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean log_2 ratio (ML2R). The authors inferred that the use of Big Data can certainly be useful for predicting the duration of interventions in the operating room and that the ML models perform better than the naïve model.

To the best of our knowledge, there is no public dataset about case duration including patients' anamnestic data. Moreover, the data coming from the EHR is often unreliable due to human errors and rough approximations. This is what prompted us to implement a new methodology for collecting times in the operating block and creating a consistent and high-quality dataset.

3. Background

To correctly collect data suitable for the application of a machine learning algorithm, we first had to choose how to gather noiseless patients' data and how to use them. Currently, Times and patient movements within the operating block are often collected manually by the operators involved and subsequently uploaded into computer systems. However, this approach is often partial and mostly does not occur in real-time. Instead, having the possibility of a direct recording, with minimum human interference, could increase the quality of the dataset and therefore provide more precise results.

To understand which technologies were the best for tracking patients during a surgical operation, we took into account three major constraints: ease of installation, devices' battery life, and reuse. In light of this, we analyzed several tracking technologies:

- RFID (Radio Frequency Identification) is an automatic identification technology based on the propagation of electromagnetic waves. This technology needs cumbersome structures for tracking and has a limited range of action. This drawback could bring discomfort to the working staff. Moreover, the RFID devices' battery life is not long enough for our case study [20].
- UWB (Ultra Wide Band) and GPS: UWB is a technology for the wireless transmission of data and information. It uses a wide band of regulated and non-regulated frequencies to transmit short-range data packets. This technology is very precise and can track the patients' movement very well in an indoor scenario. However, the GPS signal is very difficult to receive in a shielded environment like an operating room. Moreover, the UWB devices have a really low battery duration life [21].
- BLE (Bluetooth Low Energy) is a wireless technology widely applied in the Internet of Things (IoT). BLE technology operates over two main channels: advertising and data. BLE detectors are usually small and easy to install, the devices' range of action is very wide, and the tracking devices' battery charge can last even a few months [22].

4. Data Collection

To collect patient tracking data in the operating compartment minimizing human error, we developed an IoT architecture to perform indoor localization of patients in the operating compartment. In particular, the environment within which we installed the architecture is so-called the "operating block" (OB). It consists of two main sub-environments: the operating room, where the surgical operation is performed, and the recovery room, where the patient is monitored after the operation until he/she awakens. We used BLE as tracking technology for the above-mentioned reason. A BLE tracking system also provides economic advantages; hence, it does not burden the hospital budgets and is cost-effective.

The architecture can track the movements of patients within the OB. The data thus collected will form a dataset that can be used to perform ML tasks. By combining the tracking data with those of clinical assessment, it will be possible to create an algorithm capable of predicting the duration of a specific surgical intervention. Furthermore, our use case does not involve tracking healthcare staff, but only patients.

Patients are tracked thanks to a personal transmitter (BLE dongle) when entering the operating block. Tags are detected by Raspberry Pi devices (detectors) that are located in the environment of interest. Detectors communicate with a private Local Area Network (LAN) in order to manage our data flow and provide additional security levels. We realized a client-server architecture that provides communication between the sensor modules and the server in our system.

In this section, we describe our solution for monitoring patients' movements inside the operating block. Figure 1 shows the underlying logical outline of this pilot study.

The central server indexes and collects the data coming from the sensor modules, fulfilling the following duties: a) storing records coming from each detector in a MongoDB database; b) coordinating the distributed solution and message exchange using a publish-subscribe mechanism based on MQTT and, finally, exposing a web server that act as the only interface between the software architecture and the hospital operators. The central server hosts the eclipse mosquitto-based MQTT broker. When it receives the packets from the sensors, it determines that the beacon is in the room where the sensor is located. Our beacon server is implemented as a Python-based service and exploits the MongoDB database to store the various detections. The central server also has the duty to send the edge modules information, regarding the list of pre-registered beacons, the identity of the sensor itself, and a time-synchronization message.

Moreover, our architectural framework is structured to incorporate a distribution of several agents, facilitating effective management of workloads. Such modular structure ensures optimal utilization of resources and enhancing overall system performance. In order to do this, we implemented the following agents:

- Data Collection Agent:
  - The data collection agent is responsible for collecting data from BLE bangles and Raspberry Pi devices it manages data retrieval and initial processing. Every Raspberry Pi device owns a personal data collection agent.
- Data Processing Agent:
  - The data processing agent processes the raw data collected from sensors. This includes tasks like filtering, data formatting, and initial analysis.

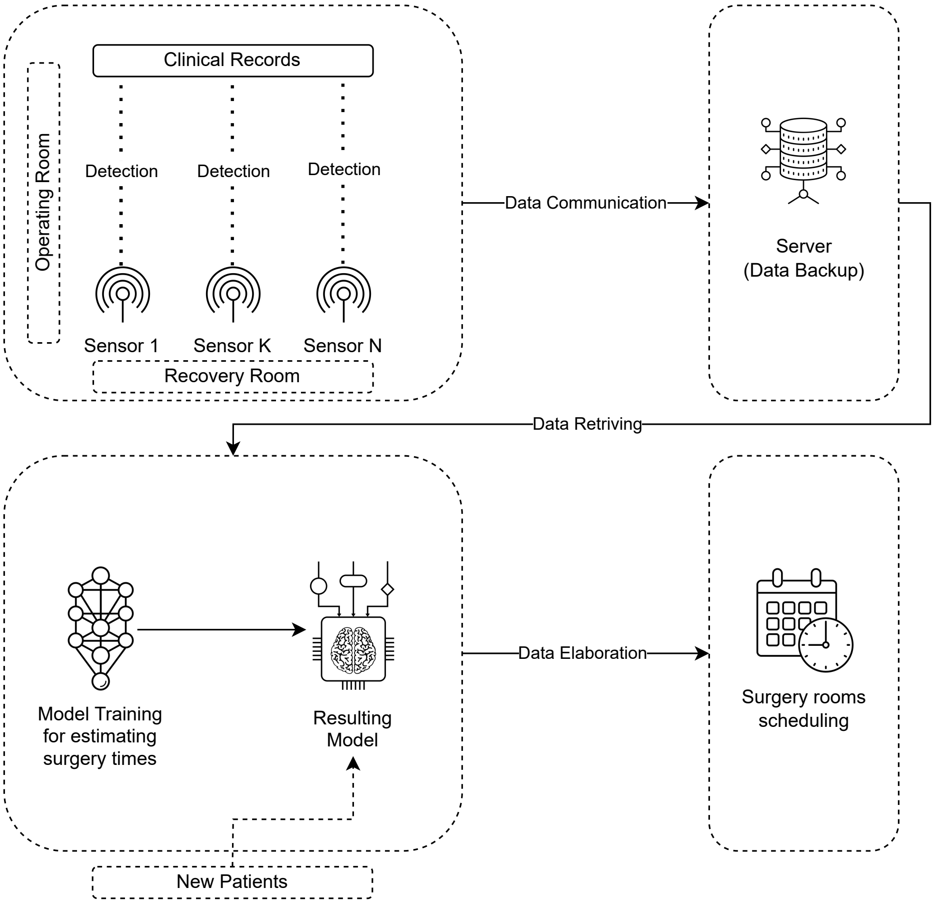

Figure 1: Logical outline of the implemented architecture.

- Location Tracking Agent:
  - The location tracking agent calculates and updates the real-time location of patients within the operating block based on sensor data. It coordinates data from multiple sources to determine accurate patient locations.
- Alerting and Notification Agent:
  - The alerting and notification agent monitors patient movements and triggers alerts or notifications based on predefined rules.
- Communication Agent:
  - The communication agent facilitates communication between Raspberry Pi devices and the central control server. It manages data transmission and reception.
- User Interface Agent:
  - The user interface agent manages the user interface through which healthcare staff can monitor patient movements. It provides a user-friendly interface for real-time tracking and control.

- Analytics Agent:
  - The analytics agent performs historical data analysis, generates reports, and provides insights into patient flow and resource utilization. It helps in identifying patterns, optimizing processes, and making informed decisions.
- Security Agent:
  - The security agent oversees system security, including access control, encryption, and threat detection. It ensures that the operating block management system is secure from unauthorized access or malicious activities.

The agents' distribution in this particular framework represents a crucial paradigm in contemporary system design. The ability to effectively manage workloads through the collaboration of multiple agents not only enhances system performance but also introduces resilience and adaptability. While challenges such as coordination and security must be addressed, the potential benefits make distributed architectures a foundation in the development of robust and scalable systems.

5. Preliminary results

The architecture has been installed in the OB at "Ospedale Maggiore di Parma", in a real use-case scenario. After an initial short testing and tuning period, we are able to present some preliminary results that prove the quality of our tracking system.

We gathered and collected data from 120 patients, and we compared times collected in the EHR with the ones coming from our BLE architecture. We considered three different cases: the total time spent inside the operating block (OB), the time spent in the operating room (OR), and the time spent in the recovery room (RR).

Considering the BLE data as the "ground truth" Table 1 reports the root mean squared error (RMSE), the mean absolute percentage error (MAPE), and the standard deviation (STD), between data coming from the BLE architecture and data from the EHR (times are expressed in minutes). Moreover, Figure 2 reports the graphs of the differences of times (in minutes) between BLE and EHR data in OR, RR, and OB, for each recorded patient, and the corresponding distribution error. In the time differences representation, times are sorted according to the value of differences for better graphical visualization. A positive value indicates that the data recorded in the EHR is underestimated, while if negative, it is overestimated.

In light of the results obtained in terms of RMSE and Percentage Mean Error, we can assert that our architecture significantly reduces the errors of manually acquired EHR records, because records collected in the EHR are noisy due to human errors and rough approximations. Moreover, the time difference expressed in MAPE ranges from 11.48% in OB, to 16.09% in OR, and even 39.79% in RR. Finally, our results highlight that the data recorded in the EHR underestimate the occupation of OB up to 59.66% of the time and overestimate it by up to 23.53%.

We considered data with an error of ± 5 minutes in line with the BLE detection.

BLE - EHR	RMSE	MAPE	STD
Total occupation time - Operating Block (in minutes)	67.672	11.48 %	65.918
Operating room occupation time (in minutes)	30.515	16.09 %	29.405
Recovery room occupation time (in minutes)	31.248	39.79 %	31.212

Table 1
Comparison in terms of root mean squared error, mean absolute percentage error, and standard deviation between times recorded by the BLE architecture and those in the EHR recorded by the medical staff (times are expressed in minutes).

6. Conclusions

Surgery has a great impact on the health economy; thus the optimal management of the resources destined for the ORs becomes crucial. Considering the existing Literature and our preliminary results, it, therefore, seems possible to assume that the application of AI models to the context of ORs management, associated with a patient indoor traceability system, is not only feasible but could also lead to a more performing scheduling.

The future developments that this scenario opens up are manifold. Once a large dataset is collected, machine learning techniques and algorithms will be evaluated as tasks that will estimate the surgery's time and/or recovery room occupancy based on pre-operative patients' anamnestic data, the type of surgical operation that had to be performed, and the optimal composition of the medical team involved in the operation. Moreover, we could also consider the use of explainable AI to understand which inputs affect the output the most.

In conclusion, this architecture allows to creation of a consistent database, which can be used by the AI methods to infer surgical times, in particular those coming from the OR, and therefore create a fine-tuned scheduling system, optimizing resources and costs.

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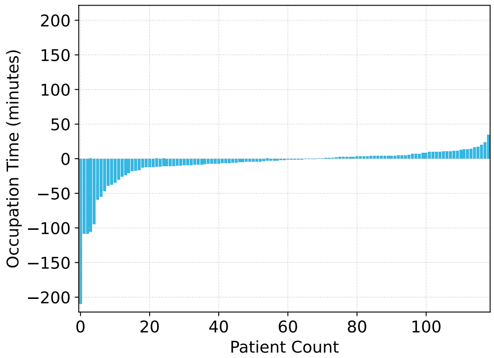
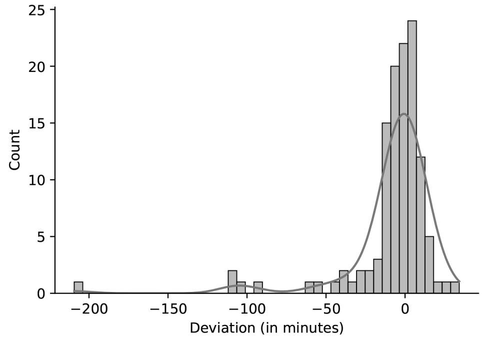
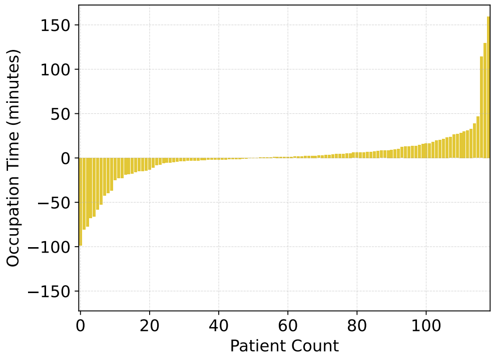


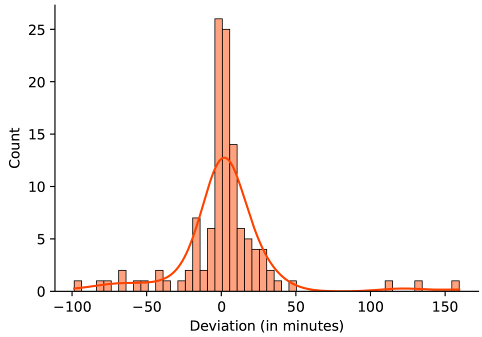
(a) Operating Room time differences



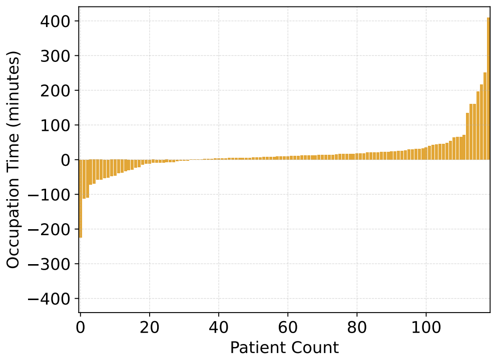
(b) Operating Room error distribution



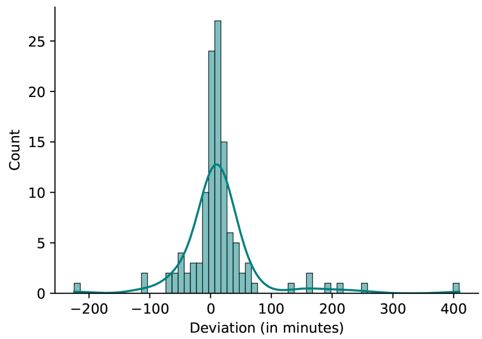
(c) Recovery Room time differences



(d) Recovery Room error distribution



(e) Operating Block time differences



(f) Operating Block error distribution

Figure 2: Sorted representation of data according to the value of differences between BLE and EHR data in OR, RR, and OB (in minutes), for each recorded patient, and the relative error distribution. In (a), (c), and (e), positive values indicate an EHR underestimation, and negative ones an overestimation, proving the low reliability of EHR data.

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