

Detecting and Analyzing the Surgical Workflow to Aid Human and Robotic Scrub Nurses

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INTRODUCTION

Every surgeon and nurse involved in surgery builds a mental model of each type of surgery based on their experiences. This implicit knowledge about the surgical workflow allows them to make decisions based on the current context and predict and prepare future steps. Acquiring this model takes time, therefore experienced scrub nurses are in high demand. Additionally to that, qualified scrub nurses are chronically scarce even in developed countries, which led to the development of robotic surgical assistants. In this paper we give a short introduction to surgical workflow analysis and show, how these methods can be applied to support both the education of human scrub nurses, as well as aid robotic scrub nurses.

The field of surgical workflow analysis or surgical process modelling has developed in recent years with the goal to enable context-awareness in the operating room of the future [1, 2]. Current approaches to recognize the surgical process involve among other methods manual labeling [3], sensor-based instrument detection [4], evaluation of the laparoscopic video [5], and kinematic data from surgical robot systems [6]. The collected data is then usually turned into a specific model through different techniques, like Dynamic Time Warping (DTW), Hidden Markov Models (HMM), or machine learning approaches like Support Vector Machines (SVM) or random forests [4, 5, 7].

The idea for Scrub Nurse Robots (SNR) has also been in development for several years [8]. Most systems rely on voice commands from the surgeon or another nurse to reach for instruments [9, 10], but one could argue that the state models used internally for the robots are already a step towards a surgical model. Enhancing these systems through surgical phase detection and automatic predictions of upcoming instrument requests would further improve the robots performance as it could then also prepare future actions, much like experienced scrub nurses do.

This paper builds on the previous work in [4], so we will apply random forests on instrument detection data in order to recognize workflow phases during a surgery. We will use this information to deduce for every step in the surgery the most probable instruments to be requested next by the main surgeon. This allows scrub nurses to prepare these instruments and provide them in time, while robotic scrub nurse systems can use this information also to optimize recognition of commands and actions from the main surgeon.

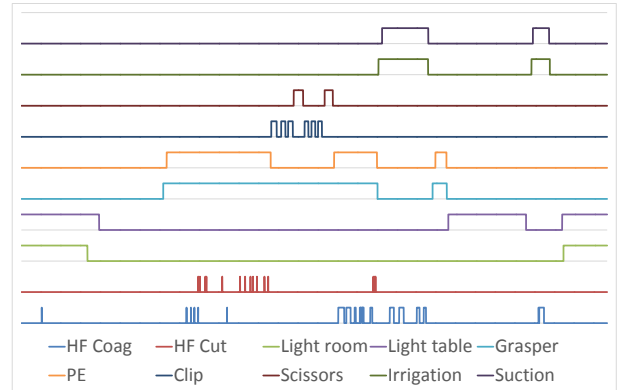


Fig. 1 Binary data collected over the course of a surgery. Each instrument or mode is in use, when the corresponding line is raised.

MATERIALS AND METHODS

Our medical application will be a laparoscopic cholecystectomy. The recorded data consists of measurements of the irrigation and suction bag weights, intra-abdominal CO₂ pressure, the inclination of the surgical table, and binary data for the state of both HF modes, the room and surgical lamps and usage of up to eight RFID-enabled surgical instruments as described in [11]. An exemplary visualization of the binary signals collected over the courses of a single surgery is given in figure 1.

We employ random forests to predict for every step of the surgery in which phase it happens. A random forest is a collection of randomly decorrelated decision trees. Each tree consists of internal nodes that evaluate simple thresholding functions on presented feature vectors. The feature vectors in our case are the collected measurements for a single timeframe. The hierarchical combination of multiple decision nodes leads to a classification of the given feature vector to one of several possible classes, in our case the a priori known workflow phases. Combining multiple classifications from several trees through a majority voting yields the final classification result of the full random forest. A more detailed explanation is given in [12].

RESULTS

Our dataset consists of four fully labeled surgeries with a total of approximately 60,000 measurements. We evaluate our classifier in Leave One Surgery Out (LOSO) fashion by training on three surgeries and validating on the forth, for each surgery. Phases could be detected by our approach with an overall accuracy of 68.78% and an

average recall over all classes of 73.41%. Detailed performance measurements per phase are given in table 1.

In a different approach we trained the forest in order to detect the expected state of the lights in the OR instead of surgical phases. The training was done after removing the light data from the training set. In this reduced scenario we reach an accuracy of 87.57% with an average recall of 75.44%

Phase	Precision	Recall
Trocar placement	99,99%	99,52%
Preparation	68,83%	79,36%
Clipping	42,54%	40,50%
Detaching gallbladder	77,89%	11,34%
Retrieving gallbladder	98,06%	99,74%
Stop bleeding	18,52%	83,49%
Drainage and closing	99,85%	99,89%

Table 1 Recognition rates for all defined workflow phases over four surgeries.

DISCUSSION

Through very simple sensor measurements we are able to detect the current phase in an ongoing surgery. Single phases still have low recognition rates that require further improvements, but as important implication one can argue that the broad application of simple and cheap sensors to the OR can provide the infrastructure for detailed workflow analyses.

For every phase there are usually at most two instruments being changed. By being able to recognize the surgical phases, we can therefor easily predict the two instruments most likely to be exchanged soon. In addition to the prediction of the light state, we can now support both the scrub nurse as well as the circulator by presenting them with their most likely next task. This allows novice nurses to be prepared and reduces the time to switch between instruments, and visualizing the progress of the surgery can improve their learning process and aid them in building their own mental model of the surgery.

In a similar manner scrub nurse robots can be supported. For a two-step system as in [9], where the SNR takes requested instruments from a full tray and delivers them to an interchange tray for a human nurse, the most likely instruments can already be provided solely based on the surgical process. In this scenario the nurse only needs to request special tools in case of emergencies or other deviations from the regular workflow and can otherwise focus on the provided, context-dependent subset of all instruments that is available on the interchange tray. But also the performance of a SNR that interacts directly with the surgeon can be improved by knowledge of the surgical progress. As stated in the conclusion of [10], inclusion of surgical process models can enable context-sensitive devices (such as scrub nurse robots) to predict upcoming steps and react to requests and common situations in smarter ways.

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