Ontology Based Surgical Subtask Automation

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***Abstract*— Streamlined integration of computer technologies into the surgical domain promises to open new opportunities in developing surgical techniques. Surgical Process Models (SPMs) and surgical ontologies currently under development are believed to make objective assessment and planning possible in the surgical practice. By automating subtask level ontological terms, these methods can be reused in a variety of surgical procedures, bringing autonomous surgery closer. In this work, the subtask level ontological term blunt dissection has been implemented in a computer vision-driven manner to demonstrate that automation on this level is feasible. Linking further building blocks of surgery could mean the beginning of automated functions for surgery.**

I. Introduction

Automation in the field of medicine is already present in many forms [1]–[5]. Most fields apply specific guidlines, such as diagnostic and treatment plans making medical decision making and practice in these fields an automated process. On this high level, with predefined treatment plans for the common diseases, automation is part of the surgical field as well, however with the rapid development of Minimally Invasive Surgery (MIS) and especially Computer Assisted Surgery (CAS), automation is penetrating into the fundamental layers of surgical practice, sometimes even replacing the surgeon's hand.

It can be easily recognized that while every surgery is different, the surgeon has one initial plan which he/she later modifies to suit the patients individual characteristics. Based on this realization, the first proposals to describe surgical operations as a sequence of tasks were published in 2001 [6]. This work established the term Surgical Process (SP), which has been defined as "a set of one or more linked procedures or activities that collectively realise a surgical objective within the context of an organisational structure", along with the term Surgical Process Model (SPM) as "a simplified pattern of an SP that reflects a predefined subset of interest of the SP in a formal or semi-formal representation" [7]. The development of SPMs required the accurate description of agents in surgery, and therefore resulted in the creation of complex data/knowledge representation systems. These are called ontologies having the potential of accurately representing surgical procedures in a way that it can be automatically analysed, and therefore domains of surgery (previously known to be very subjective, such as skill assessment) can be objectively measured [6]. Besides skill assessment (as [8] realized) ontologies actually have a wide usability spectrum including:

- Evaluation of tools/surgical approach/systems,
- Surgical education and assessment,
- Optimisation of OR management,
- Context-aware systems and
- Robotic assistance.

SPMs can describe surgery in many levels of granularity, starting from the task level to the finest level recording the surgeon's motion primitives [9]. On the higher granularity levels, critical and time consuming steps of the surgery can be analyzed, where the finer level of detail gives less information on the procedure performed, instead it can be used to evaluate the surgeons economy of movement, gaining information on the surgeons manual skills [10].

For this work, ontologies have been used to brake down surgical procedures into the subtask level. This level of granularity uses surgical actions (such as "ligating", "cLipping", "dissecting" etc.), therefore most of the terms are not procedure specific. If these terms can be successfully automated then they provide an abstract enough representation to later serve as building blocks for a multitude of surgical procedures. Low granularity levels (surgical motion primitives) were also considered as possible building blocks. Previous works have demonstrated that automation is possible on these levels where surgical robots perform reaching, pulling, cutting and other primitive motions to achieve a well defined goal [3]. We found that these low granularity level applications are not feasible to be used as surgical building blocks, mainly because inter-patient variability makes their target goals—in real world scenarios—hard to define, and therefore they are not feasible to build SPMs. Furthermore, as [10] showed expert surgeons use fewer movements compared to novices and residents, therefore, instead of focusing on the reproduction of surgical motions, subtask automation should aim for minimizing tool motion.

II. Materials & Methods

For this work, Laparoscopic Cholecystectomy (LC) has been chosen as the targeted procedure, and has been described (based on the surgical literature and video recordings

*The research was supported by the Hungarian OTKA PD 116121 grant.

*This work has been supported by ACMIT (Austrian Center for Medical Innovation and Technology), which is funded within the scope of the COMET (Competence Centers for Excellent Technologies) program of the Austrian Government.

*Supported through the New National Excellence Program of the Ministry of Human Capacities

*We acknowledge the financial support of this work by the Hungarian State and the European Union under the EFOP-3.6.1-16-2016-00010 project.

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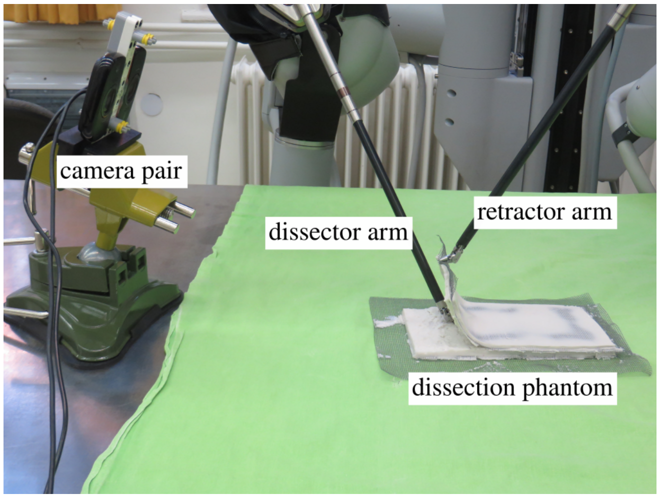

Fig. 1. Automatized blunt dissection test setup. The da Vinci Surgical System, a dissection phantom and a stereo camera pair was involved.

of the procedure) at the subtask level. From this description, the ontological term of ”blunt dissection” has been selected as targeted subtask for further examination. In our framework, this term is handled as an atomic executable task, where the algorithm filling this block defines the set of required sensory inputs to successfully control and monitor the execution of the process.

A. Blunt dissection

Blunt dissection is a process where the surgeon intends to separate two layers of loosely connected tissue without damaging either layers. In this procedure, the dissector is gently inserted between the two layers, then the opening of the dissector forces the two layers apart, while braking only the more fragile connective tissue between the layers.

During LC procedures, blunt dissection is used to open up the Calot triangle without damaging the anatomical structures.

To test our automated blunt dissection algorithms a special phantom called the ”bacon” was created. The bacon consists of two layers of silicone and between them a layer of softer, foamy silicone. This intermediate layer can be penetrated with the laparoscopic tool, and dissection can be carried out.

B. Computer vision

During robotic minimally invasive (da Vinci-type) laparoscopic surgery, the most common—in some cases the only—sensory input is the frames from the stereo endoscopic camera. Due to this fact, we decided to base our algorithm only on the video feed, and not reling on additional sensors. This approach models the surgeon’s behavior, and more importantly, does not put additional overhead on the OR equipment, making the algorithm easily integratabtle into current surgical procedures.

During the experiments, sensory input was gained from two low-cost webcams *(Logitech C525)*. The cameras were placed in a stable frame with 50 mm base distance from each other. The blunt dissection phantom was fixed on a stiff surface, approximately of 250 mm distance from the stereocamera. The computer vision method was implemented in MATLAB 2016b.

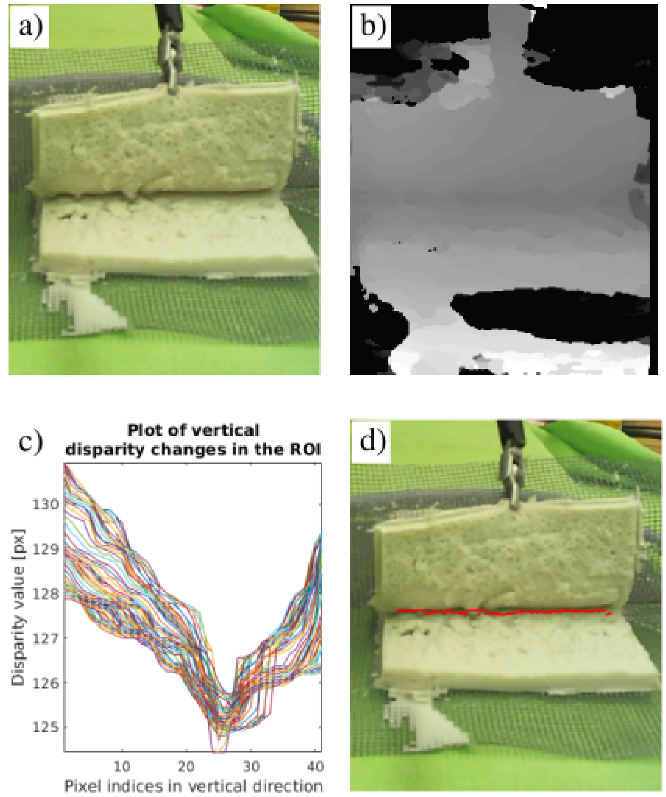

Fig. 2. Automation computer vision based blunt dissection. a) stereo camera image of blunt dissection phantom; b) disparity map of the field of view; c) plot of disparity changes in vertical direction; d) blunt dissection profile from the local minimas of the disparity.

To have the autonomous blunt dissection algorithm running as precisely as possible, it is essential to gather an accurate 3D representation of the dissection profile. To achieve this, the stereocamera needs to be calibrated and the stereo images rectified before the task execution.

The algorithm starts with the user initializing the start and stop points of the blunt dissection line on the initial (2D) view. This step serves to define the region of interest for the program, because the observed surgical field (most of the times) contains many potential areas where blunt dissection can be carried out. From the stereo rectified grayscale images the program calculates the disparity map, using the Semi-Global Block Matching Algorithm. This algorithm employs pixelwise matching based on Mutual Information and the approximation of a global smoothness constraint [1]. Between the initialized start and stop points, the program defines the precise dissection target points. These target points are identified by searching for the local minimas on the disparity map on the line between the initialized boundary points. This search for local minimas is executed on the plane perpendicular to the dissection line. If the method did not find peaks or the disparity values were invalid, the algorithm uses the initialized start point and the disparity values of its

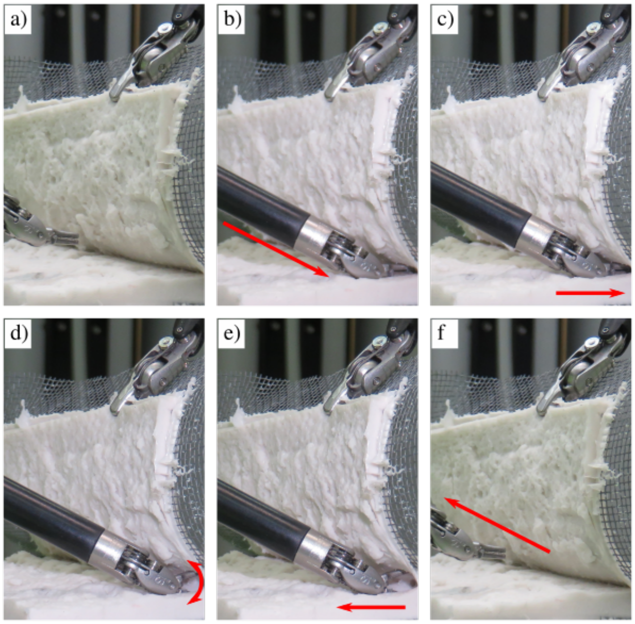

Fig. 3. Robot movements of the surgical subtask automation. a) The surgical instrument moving to the dissection target; b) push the instrument into the phantom; c) open the tool; d) pull out the instrument and move to the next target.

location. The algorithm was further improved with a feature, where it finishes the blunt dissection after the surgeon has started it. It is essential that the algorithm determines the tool orientation correctly, so it is close to parallel to the dissection tissue surfaces. This is based on the dissection profile; after the target of the surgical instrument is determined, the tool's orientation is calculated from the disparity values of the local environment of this target.

C. Robot control

In the presented automatic blunt dissection method we used the da Vinci Surgical System alongside with the da Vinci Research Kit (DVRK), which provides an open ROS interface to the robot [11], [12]. We choose the da Vinci Surgical System, because it is widely used in the everyday clinical practice worldwide, with yearly more than 500 000 procedure performed only in the US.

To achieve accurate tool movements based only on the visual information, first, the transformation between the coordinate system of the robot and the camera is determined (hand–eye calibration). We use a checkerboard method, where a small, easily detectable checkerboard pattern is attached to the tooltip [13]. Images were captured by both cameras simultaneously in different tool positions, and tool coordinates were calculated from the detected checkerboard positions on the image pairs. Simultaneously the cartesian positions are also received from the DVRK in the robot's coordinate system, after which the transformation between the two coordinate frames are calculated by rigid frame registration.

To dissect the two layers of tissue, the top layer is placed

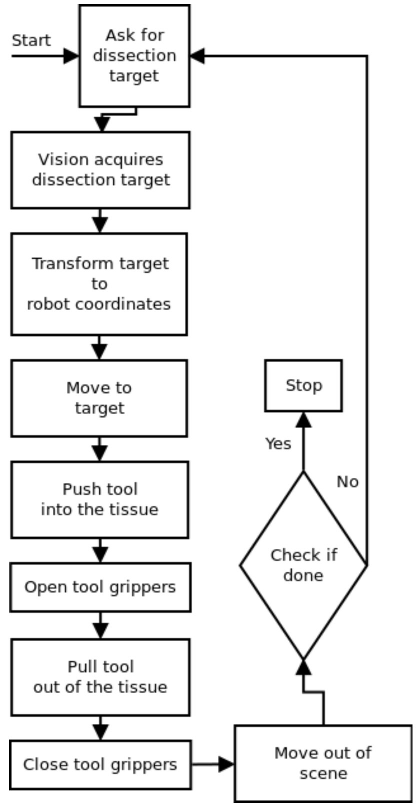

Fig. 4. Flow diagram of the blunt dissection automation method. The image based input defines the targets of the blunt dissection; based on this information the robot can perform the blunt dissection surgical subtask.

under a constant retraction force. At this point of the development this is done manually with another da Vinci arm. The workflow of the automatic blunt dissection subtask starts by finding the target on the phantom. The dissector arm then approaches the target, and the tool is moved into the penetrable tissue between the two hard silicone layers. When the tool finished the penetration of the dissectible tissue, the grippers are opened and the tool is pulled out (remaining open until it left the phantom). The process separates the two tissue layers in the tool's small local region. After this series of movements, the grippers are closed and the tool is moved out of the scene so it is not blocking the the camera view, and a new stereo image is captured. If the blunt dissection is not finished (e.g., the target structure is not exposed), a new dissection target is acquired, otherwise, the agent stops. This process is shown in Fig. 4.

III. Results

The method was tested on the above described phantom. The dissection progressed on the intended dissection line in all the test cases. For dissection an endowrist "large needle driver" instrument was used, and the procedure progressed on a 10 cm dissection line with an average of 0.5 cm/min speed, and the tool placement achieved an approximated 1 mm accuracy during the tests. To test accuracy in a predefined environment, an additional test was performed in the following setup: (1) After hand/eye calibration, the toll was moved in front of the camera and the tool position was recorded on the camera 3D frame and on the robot's coordinate system, then (2) the tool was moved away, and (3) the robot was asked the reach the point on the 3D image record. (4) When the robot finished the approach the tool position was compared to the initial tool position. During this test scenario, from 10 test cases, an average of 2.2mm accuracy was achieved with a standard deviation of 0.5mm on the camera view's plane. On the depth axis the algorithm achieved 1mm accuracy with standard deviation of 0.6mm. It is worth to note however, that the tests are highly dependent on the vision system, and these results could be improved by using industry standard cameras instead of the current low-cost web-cameras. With these low-cost cameras accuracy problems were often attributed to the focusing system and to low resolutions.

IV. Discussion

The presented method utilizes readily available input parameters, making it easily integrable into current surgical applications. It has about 1 mm accuracy, but it is worth to note that additional sensory input could increase this, however, in practice sub-millimetric accuracy is not always required. By creating multiple automated methods for implementing the same ontological term, the most fitting methods can be chosen for the procedure. The algorithm presented does not automate several tasks needed for ex- and in-vivo applications. These include the automation of retraction, and the selection of start and stop criteria. In the structure presented above these are important, but separate subtask level processess, and thus, they should be developed individually. Future objectives include the implementation of "retraction", "suction", "coagulation" etc. ontological terms. Robot motions in this work were programmed manually, and while they were achieving the intended goal, in future development we intend to improve the economy of motion by implementing "learning by observation" approaches.

V. Conclusion

The example of the successfully automated blunt dissection shows that subtask level in SPMs is a low enough granularity level where ontological terms can be automated. At this level, subtasks can be defined appropriately for the machine, while not too much contextual information is lost for the human on the targets of the surgical procedure. It is also presented that in case of blunt dissection during laparoscopic cholecystectomy, the available camera input is sufficient to execute the automated method solely relying on the visual data. Further trials are necessary to confirm the reliability ad robustness of the method under realistic surgical conditions.

ACKNOWLEDGMENT

The authors would like to thank Tivadar Garamvölgyi for providing the phantom used in the experiments.

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