Tissue Deformation Tracking in Robot-Assisted Nephrectomy

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***Abstract*— Dynamical application of active constraints during robot-assisted surgery is key to safer and more precise minimally invasive surgery. In this article, the proposed method dynamically tracks the movement and deformation of the renal veins and arteries in real-time and estimates the distortion based on 2-D tracking and iterative estimation of the 2-D perspective transformation matrix. The proposed method is validated via videos taken from nephrectomy on the da Vinci Research Kit.**

Keywords*— *long-term tissue tracker, active constraints, augmented reality, image processing

A brief video of this work is available on-line at: https://drive.google.com/open?id=1mPsOThLygpTfUCD958oPvCtKpvtVFazV

I. Introduction

Despite the increasing adoption of robot-assisted surgery, surgical tasks on soft tissue remain under the manual execution of the surgeon and her/his maneuvers when reaction required at critical situations. Functional outcomes, including rates of complications and fatalities, have remained highly variable owing to human factors, such as hand-eye coordination and mainly experience. Robot-assisted surgeries are led by a surgeon while the robots act as an assistant that executing the operator commands. Adding a type of regulation to these motions at regions and situations promise substantial benefits through improved safety from the reduction of human errors and increased efficiency.

In a Minimally Invasive Surgery (MIS) type nephrectomy, renal veins and arteries are the most critical parts which should be protected during a procedure. Though they are easily definable and describable preoperatively, during surgery this is not possible due to numerous physical effects. Soft tissues such as blood vessels will move and deform because of tissue manipulation, change of patient's pose, breathing and heartbeat. This requires an approach which can track and estimate these changes during surgery in a real-time manner, to be computationally feasible and adaptable.

In the last decades, assistive applications such as Active Constraints (AC) [1] for motion regulating are developing to assist surgeons. Even though these applications suffer from soft tissue movements and changes in camera orientation majority of the literature, assumes that the environment is stable enough for the use of static active constraints [2]. To overcome this lack of literature, a solution is proposed which bridges this gap and introduces the implementation of dynamical AC in Robot-Assisted MIS (RA-MIS). Once they are transformed accordingly to the real tissue deformation, the tissue protected will stay continuously inside the Safety Area (SA) which the robot will use as a constraint to its movement.

This paper is structured as follows: In Section II used methods described accordingly to the phase they were used in; in Section III numerical results are described. Finally, discussion and conclusions are reported in Section IV.

II. Methods

An overview of the proposed algorithm with three main functions, optimization techniques and AC implementation will be given in this section.

A. *Proposed Algorithm*

The proposed algorithm will be introduced in three sections, respectively. In addition optimization techniques will be discussed. For the developing algorithm Python programming language used with OpenCV libraries.

1) *Initialization of Tracking Algorithm*

The initialization phase, or start-up, consists of providing the system with the reference AC. In addition, a model buffer which acts as a storage for SA models, is filled with the initial model for further autonomous localization and redefinition of the AC in the case of tracking performance drop.

2) *Tracking Algorithm*

Once initialized, tracking is applied between the latest two concurrent frames. Preprocessing is required to handle environmental noise while preserving morphological definitions of the tissue. A combination of edge detection [3] and feature detection [4] are used to adapt each frame for the particular application in this method and used as input into Lucas-Kanade (LK) tracking algorithm [5]. Actively model buffer is being updated with new and well-posed models.

A performance metric is used for detecting when tracking performance has decreased below a threshold. When it drops below this threshold, automated AC localization and re-definition are done.

3) *Re-Initialization Algorithm*

Using a combination of template matching and feature matching, models stored inside the model buffer are matched to the current frame to localize the tissue. Upon acquiring a good enough estimation of where the tissue is, morphological snake algorithm [6] and several binary filters are applied to redefine the AC concerning color definitions and morphology.

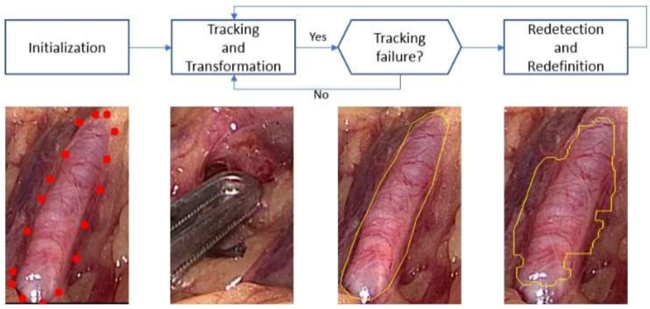

Fig. 1. Flow-chart of the proposed method.

4) *Optimization Techniques*

Providing a method which will be used in a real-life surgical application requires precision and real-time execution. To achieve these, several possibilities described in the following were exploited:

- Template matching in re-initialization is done in parallel;
- Template features are stored in the buffer to reduce workload;
- Caching of numerical functions for instant execution at the following call;
- Image is compressed with bilateral interpolation.

B. Method for Implementing Dynamic Active Constraints

Proposed algorithm, relies on the 2D images. Although AC, regulates the motion of robot in 3D space, 3D constraints can be projected onto the 2D plane for constraint evaluation [1]. Thanks to projection, 3D constraints can be followed and updated with respect to the 2D imagery. Surgeon can define AC by using an input device to draw contour over a projected plane of 3D constraints point cloud.

III. Results

Performance results are from 25-fps two videos of nephrectomy procedure using DaVinci Research Kit, provided by a consulting surgeon. The process is real-time.

A. Performance of Tracking and Re-Initialization

Redefinition of AC performance criteria was based on the Jaccard similarity coefficient, by calculating the set difference of the binary AC contour before and after binary filtering (especially affected by erosion). In the following table, the mean value and standard deviation of the Jaccard index, as seen in the paper of Niu et al. [7] in redefinition for both tests are shown. Both videos were cut to exclude large portions with the reappearance of the tracked tissue.

As seen in Table I, means of 0.79 and 0.84 suggest to good approximation considering 0 is no match at all and 1 is a perfect match between two sets, and a standard deviation of 10% of the full range is acceptable by the fact that it points to a minimal expected Jaccard score of 0.7 or a 70% match in the worst-case scenario.

TABLE I. Jaccard index distribution

	Mean	Standard Deviation
Video Sequence 1	0.84	0.09
Video Sequence 2	0.79	0.11

Tracking performance criteria was based on length of active tracking without re-initialization. This gives a representation on how the tracking is robust to the high dynamics of the video concerning object movement, change of lightning, change of focus and partial occlusion. Tracking timespan, as shown in Table II, in a fairly dynamic environment like the one which can be observed in the second video of 7.7 [s], and respectfully of 11.2 [s] in a less dynamic video, proves that the proposed method is well-posed for long term tracking.

TABLE II. Tracking time length

	Longest [s]	Average [s]
Video Sequence 1	11.2	4.8
Video Sequence 2	7.7	6.1

By semi-automatic labelling, each frame in the video sub-sequences to define ground truth [8], Precision and Recall were calculated where the overlap metric between this method's redefinition result and the ground truth is Jaccard index. In Table III, first column presents the Precision score as a fraction of true positives over all retrieved positives (true and false positives) of SA detection, while the second column is Recall score as a fraction of true positive detections over total amount of all relevant instances (true positives and false negatives) of SA detection. A precision score which averages to approximately 0.85 refers to acquiring only 15% of false positives while a recall score averaging to approximately 0.785 refers to failing to detect 21.5% of visible tissue. The works of Penza et al. [9] achieved comparable, yet higher Precision and Recall scores. However, this proposed method, while acquiring slightly lower results, achieves higher fps and is real-time applicable. Tracking phase showed an average of 75 fps, and re-initialization phase, an average of 11 fps.

TABLE III. Precision and Recall score

	Precision	Recall
Video Sequence 1	0.89	0.83
Video Sequence 2	0.81	0.74

B. Outcomes of Tracking in Augmented Reality

Dynamical tracking of the AC provides adequate protection of critical tissues. Not only as tool-to-tissue distance but also will notify the surgeon through an Augmented Reality adaptation. Another positive outcome is that in a situation where the surgeon loses concentration, tracked tissue will not because the surgical tool will be blocked from accessing that region.

IV. Discussion and Future Work

In this paper, we presented an algorithm for tracking organs to improve the safety of RA-MIS by guiding the surgeon. Currently, developed algorithm depends on 2D images. We would like to extend this research by combining stereo images of endoscope. Besides, absolute camera position from the robot was not used for this paper which could be implemented to improve stability and repeatability.

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References

[1] S. A. Bowyer, B. L. Davies, and F. Rodriguez Y Baena, "Active constraints/virtual fixtures: A survey," IEEE Trans. Robot., vol. 30, no. 1, pp. 138–157, 2014.

[2] M. Li, M. Ishii, R. Taylor, "Spatial Motion Constraints Using Virtual Fixtures Generated by Anatomy", Robotics, IEEE Transactions, vol. 23, no. 1, pp. 4 - 19, 2007.

[3] John Canny, "A Computational Approach to Edge Detection", Transactions on Pattern Analysis and Machine Intelligence, vol. 6, pp 679-698, 1986.

[4] A. B. and A. J. D. Pablo Fernández Alcantarilla, "KAZE Features," pp. 1–14, 2012.

[5] J. Bouguet, "Pyramidal implementation of the affine lucas kanade feature tracker," Intel Corp., vol. 1, no. 2, pp. 1–9, 2001.

[6] T. F. Chan, B. Yezrielev Sandberg, and L. A. Vese, "Active contours without edges for vector-valued images," J. Vis. Commun. Image Represent., vol. 11, no. 2, pp. 130–141, 2000.

[7] S. Niu, Q. Chen, L. de Sisternes, Z. Ji, Z. Zhou, and D. L. Rubin, "Robust noise region-based active contour model via local similarity factor for image segmentation," Pattern Recognit., vol. 61, pp. 104–119, 2017.

[8] S. Vajda, Y. Rangoni, and H. Cecotti, "Semi-automatic ground truth generation using unsupervised clustering and limited manual labeling: Application to handwritten character recognition," Pattern Recognit. Lett., vol. 58, no. November 2018, pp. 23–28, 2015.

[9] V.Penza, E. De Momi, N. Enayati, T. Chupin, J. Ortiz, L.S. Mattos., "Safety Enhancement Framework for Robotic Minimally Invasive Surgery," no. July, pp. 51–52, 2017.