

Interactive Wound Segmentation and Automatic Stitch Planning

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INTRODUCTION

In Minimally Invasive Robotic Surgery suturing is one of the most critical and delicate tasks, even for a skilled surgeon, because of its time demanded, high dexterity required and risks of causing damage to organs and/or tissues. Several works have been proposed, in the last years, to help the surgeon during this task. For instance in [1] and [2], an automatic multi-throw framework and a supervised paradigm have been developed to investigate fully autonomous and supervised suturing procedure. To adapt the suturing planner to environment changes, e.g. wound motion and deformation, the wound needs to be tracked on-line. In literature, some methods have been proposed relying on edge and color based segmentation [3] or Near-Infrared Fluorescent (NIRF) markers [2]. In this work, we propose a simple and efficient GrabCut-based wound segmentation method and an automatic stitch planning that can be used to on-line obtain the optimal stitch poses.

MATERIALS AND METHODS

Consider a suturing procedure composed of N stitches, the k -th stitch can be defined as a circular trajectory, for the needle tip, from the point a_k to b_k in the stitch frame $O_{s,k}$ ¹ (see Fig. 1). $O_{s,k}$ can be defined by choosing: (i) the axis $\mathbf{x}_s$ along the direction from $\mathbf{x}_{e,k}$ to $\mathbf{x}_{i,k}$ (extraction and insertion points); (ii) the $\mathbf{z}_s$ axis along the tissue normal unit vector $\mathbf{n}_k$, (iii) the axis $\mathbf{y}_s$ to have an orthonormal frame; (iv) the frame origin in the center of the circle, with radius equal to the chosen needle radius r , passing through the points $\mathbf{x}_{i,k}$ and $\mathbf{x}_{e,k}$. Hence, each stitch k can be uniquely defined by the n-upla $s_k = [\mathbf{x}_{i,k}, \mathbf{x}_{e,k}, \mathbf{n}_k, r]$ extracted from the wound shape. In this work we model the wound using: (i) a central spline ($\Sigma_c(\sigma)$) defining the wound shape, (ii) two lateral splines ($\Sigma_r(\sigma)$, $\Sigma_l(\sigma)$) defining two guides for the stitch insertion and extraction points, (iii) a parametric unit vector $\mathbf{n}(\sigma)$ locally orthogonal to the tissue².

Each stitch s_k have been calculated by equally spacing N points imposing a relative 25% of overlap between the stitches: $N = \lceil 1.25l/D \rceil$ where, both the

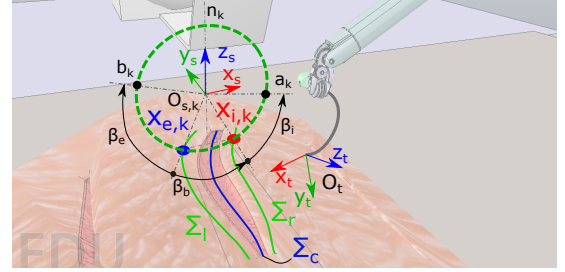


Fig. 1: Stitch plan. β_i/β_e : insertion/extraction angles wound length l and the wound depth D are obtained on-line respectively from the length of the central wound spline and the average distance between the wound borders.

Wound segmentation and registration

Using the force measure, obtained using our trocar force sensor [4] and the surgeon's visual perception in the loop, we design an effective method to interactively initialize the wound pose. In details, the wound initialization is obtained by touching the tissue at the beginning and at the end of the wound, moving along the wound shape. All the collected points are smoothed using a spline and used to initialize the segmentation by defining a set of pixels belonging to the foreground.

To on-line segment the wound we rely on the efficient and widespread GrabCut method [5]. The GrabCut algorithm addresses the visual bilayer segmentation task as an energy minimization problem, based on statistical models of the foreground (FGD) and the background (BGD). For an input image, we denote by $\alpha = [\alpha_i]_{i=1}^N$ the set of the unknown binary labels of the pixels ($\alpha_i = 0$ for the BGD pixels, $\alpha_i = 1$ for the FGD). Estimating the values $\hat{\alpha}$ of an unknown pixel can be formulated as the minimization of an energy-based Markov Random Field objective function

$$E(\alpha) = \sum_i (U_i(\alpha_i)) + \gamma E_s(\alpha)$$

with respect to α , where, E_s is a smoothness energy term, γ is a gain, and $U_i(\alpha_i)$ is a term accounting for the observation probability $p(\mathbf{p}_i|\alpha_i)$ for a pixel $\mathbf{p}_i$ to belong to the FGD or to the BGD. In our implementation this term is computed as Gaussian Mixture Models (GMM), based on image color distribution, learned, during the initialization process, for both the FGD and BGD layers.

¹The stitch and PSM base frame has been calibrated w.r.t. the camera frame using a standard hand-eye approach

² $\sigma \in [0, 1]$ is the curvilinear abscissa.

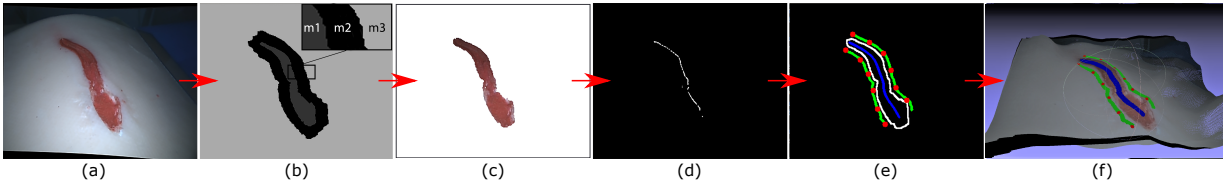


Fig. 2: Snapshots: (a) initial image, (b) segmentation trimap mask, (c) segmented image, (d) wound skeleton, (e) wound model and stitching points overlapping, (f) registration onto the 3D point cloud. In (e,f) the central spline is indicated in blue, the lateral splines are indicated in green while the stitch points are indicated in red.

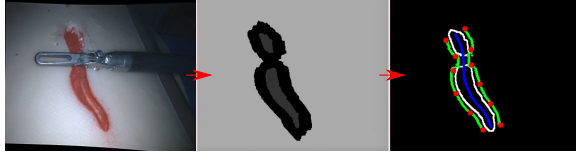


Fig. 3: Robustness w.r.t. partial occlusion occurrence.

Once the initial image is segmented through user interaction, the following frames are evaluated by considering a defined mask. In details, from the previous segmented foreground, we calculate the distance transform, providing a signed distance map. On this distance map, we define a narrow strip composed by three areas (trimap) with different probabilities of the pixels to be FGD or BGD. With reference to Fig. 2 (b) we have been defined. m1: $U_i(\alpha_i = 1) = \inf(\text{FGD})$; m2: $U_i(\alpha_i = 1) = -\log(p(\mathbf{p}_i|\alpha_i))$ (probably FGD/BGD); m3: $U_i(\alpha_i = 0) = \inf(\text{BGD})$. In this manner, temporal consistency is ensured, since energy minimization is only effective within the strip in the vicinity of the previous segmentation boundary, avoiding some outliers outside or inside, and reducing computations [6].

From the segmented image, the straight morphological skeleton of the polygon has been extracted³. The role of the skeleton is to account the topological structure of the incision. Moreover, the wound contours have been extracted relying to well known Open-Cv functions (*Canny* and *find contours*). Hence, we fitted: (i) the image central spline $\Sigma_{c,i}(\sigma)$ on the skeleton points; (ii) the two image lateral splines ($\Sigma_{r,i}(\sigma)$, $\Sigma_{l,i}(\sigma)$) by a defined offset w.r.t. the wound contours points belonging to the central spline normals unit vectors in the image plane. Finally, by resorting on the efficient stereo (ELAS) approach [7] the 3D point cloud of the tissue has been calculated. From the point cloud we obtained the wound normals $\mathbf{n}(\sigma)$, the 3D splines ($\Sigma_c(\sigma)$, $\Sigma_r(\sigma)$, $\Sigma_l(\sigma)$), by registering the image plane splines, and the 3D stitch points in order to have a 3D description of the wound.

EXPERIMENTS AND RESULTS

Our experimental setup is composed of the full da Vinci Research Kit commanded in teleoperation mode. All the visual computations, including the 3D point cloud generation, have been obtained using the da Vinci endoscopic cameras acquired at 30 Hz. Figure 2 shows some snapshots resulting from the

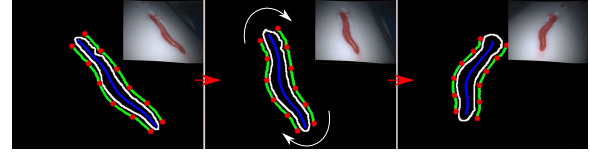


Fig. 4: Robustness w.r.t. wound motion or deformation.

segmentation. From left to right all the segmentation phases and the stitch point selection and registration have been reported in a case study tested on a suturing phantom. Moreover, in Fig. 3 we report some snapshots showing the robustness of the proposed approach w.r.t. partially occluded images. Our preliminary experiments show also the capability of the method to maintain the segmentation during the wound motion or deformation allowing a wound tracking at 10Hz (Fig. 4).

CONCLUSIONS

In this work, a wound segmentation method supported by an interactive force-enabled wound initialization and an automatic stitch point selection are presented. Preliminary experiments show good results and robustness in the segmentation. In future work, a GPU-based GrabCut algorithm will be used to improve the tracking capability.

References

- [1] S. Sen, A. Garg, D. V. Gealy, S. McKinley, Y. Jen, and K. Goldberg, "Automating multi-throw multilateral surgical suturing with a mechanical needle guide and sequential convex optimization," *IEEE Int. Conference on Robotics and Automation*, pp. 4178–4185, 2016.
- [2] A. Shademan, R. S. Decker, J. D. Opfermann, S. Leonard, A. Krieger, and P. C. W. Kim, "Supervised autonomous robotic soft tissue surgery," *Science Translational Medicine*, vol. 8, no. 337, 2016.
- [3] S. Leonard, K. L. Wu, Y. Kim, A. Krieger, and P. C. Kim, "Smart tissue anastomosis robot (STAR): A vision-guided robotics system for laparoscopic suturing," *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 4, pp. 1305–1317, 2014.
- [4] G. A. Fontanelli, L. Buonocore, F. Ficuciello, L. Villani, and B. Siciliano, "A novel force sensing integrated into the trocar for minimally invasive robotic surgery," in *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*.
- [5] C. Rother, V. Kolmogorov, and A. Blake, "Grabcut: Interactive foreground extraction using iterated graph cuts," vol. 23, pp. 309–314, 08 2004.
- [6] A. Petit, V. Lippiello, G. A. Fontanelli, and B. Siciliano, "Tracking elastic deformable objects with an RGB-D sensor for a pizza chef robot," *Robotics and Autonomous Systems*, vol. 88, no. September, pp. 187–201, 2017.
- [7] A. Geiger, M. Roser, and R. Urtasun, "Efficient large-scale stereo matching," *Asian conference on computer vision*, pp. 25–38, 2010.

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