Image-based tracking of the suturing needle during laparoscopic interventions

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ABSTRACT

One of the most complex and difficult tasks for surgeons during minimally invasive interventions is suturing. A prerequisite to assist the suturing process is the tracking of the needle. The endoscopic images provide a rich source of information which can be used for needle tracking. In this paper, we present an image-based method for markerless needle tracking. The method uses a color-based and geometry-based segmentation to detect the needle. Once an initial needle detection is obtained, a region of interest enclosing the extracted needle contour is passed on to a reduced segmentation. It is evaluated with in vivo images from da Vinci interventions.

Keywords: Surgical Vision, Localization & Tracking Technologies, Endoscopic Image Processing, Robotic-assisted surgery, Laparoscopic procedures

1. INTRODUCTION

Minimally invasive surgery (MIS) is a highly complex medical discipline where the surgeon has to deal with a complex hand-eye coordination, a restricted mobility and a narrow field of view. One of the most complex and difficult tasks for surgeons during such interventions is minimally invasive suturing. Suturing is usually done with two needle holders and a curved needle. During the suturing process, grasping the needle in the right orientation for repositioning the needle holder is extremely challenging. Due to the narrow laparoscopic workspace, the range of motion and the visual feedback is limited, even when using robotic systems like the da Vinci telemanipulator.

A prerequisite to assist the suturing process is the tracking of the suturing needle. A reliable tracking and pose estimation allows assistance functions for correct needle positioning, distance measurements between suturing needle and surrounding tissue or semi-automatic robot controlled suturing.

The endoscopic images provide a rich source of information which can be used for needle tracking. Image-based needle tracking in laparoscopic surgery is challenging due to homogeneous textures, strong specular highlights, varying lighting conditions and tissue reflection on the needle itself. Furthermore, the needle motion is unconstrained and partial occlusions occur frequently when treating tissue or by other surgical instruments in the abdomen. Up to now, there are approaches which color the needle [1,2] to distinguish it from the background or apply it in a experimental laboratory setting [3].

In this paper, we present an image-based method for markerless needle tracking. The method uses color-based and geometry-based segmentation to detect the needle. Once a stable needle detection is obtained, a region of interest (ROI) is passed to the tracking component. It is evaluated with in vivo images from da Vinci interventions.

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2. METHODS

In general, the suturing needle in endoscopic images is a metallic, achromatic component where the level of specularities on the needle frequently changes depending on illumination. An additional complexity is that the metallic surface reflects the abdominal environment, such that the needle appears reddish instead of achromatic colors. The proposed method for image-based tracking consists of a needle segmentation step followed by the tracking. The segmentation uses color and geometric information to distinguish the needle from the background. Once an initial needle detection is obtained, a region of interest enclosing the extracted needle contour is passed on to a reduced segmentation step. No marker or color-coding is applied to the suturing needle to facilitate identification of needle pixels. The single steps are explained in detail in the following sections.

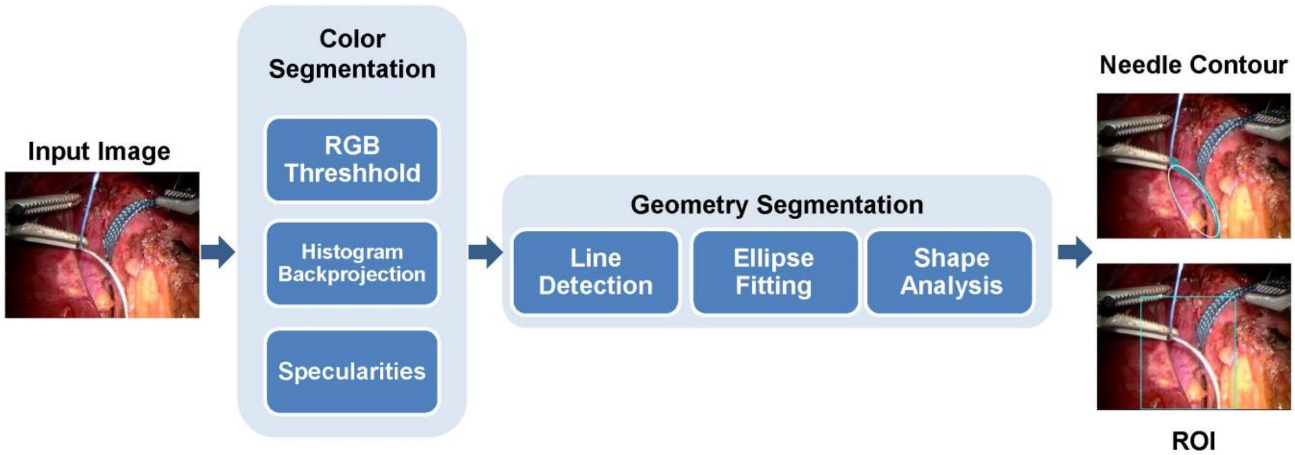

Fig. 1: Needle segmentation.

2.1 Color-based needle segmentation

Figure 1 visualizes the overall segmentation workflow. First the images are deinterlaced with a bob line interpolation approach since interlacing artefacts appear particularly in areas with motion like the instrument regions. The color segmentation involves three different visual cues taking into account the color characteristics of the needle (Fig. 2).

RGB Threshold

The first cue is a threshold filter in the RGB color space. Since achromatic colors like grey and white have nearly the same intensity value in all three channels, an image pixel p is discarded if the channel deviation exceeds a certain threshold: $p > \frac{R+G+B}{3} \pm 15, p \epsilon [R, G, B]$. In contrast, the reddish tissue pixels are dominated by a significantly higher value for the intensity in the red channel. Remaining objects are mainly the surgical instruments, the suturing needle, and dark pixels in the periphery of the image.

Histogram Backprojection

The backprojection is done in the HSV color space. The basic idea is to measure how well individual pixels of the input image fit the histogram distribution of a needle template. The template includes several needle views representing different lighting conditions and color intensities. A probability is assigned to each pixel based on comparing the template histogram and the histogram of the input image. The resulting image is smoothed and morphological operators are applied.

Specularity Detection

An important cue is specularities on the needle which are detected in the HSV color space. A pixel is marked as possible specularity if saturation (S) and value (V) are within a certain threshold range. Afterwards, connected specularity regions are detected and analyzed. If the contour size is too small or too big, pixels are discarded; otherwise the region is colored white and cannot be excluded from the fused image even if other color-based image processing steps might mark those pixels as not being part of the needle. Remaining regions are possibly located on the suturing needle.

Combining filter outputs to an aggregated color-based segmentation result leads to images containing primarily the suturing needle, further metallic objects, and specular tissue regions (Fig. 2).

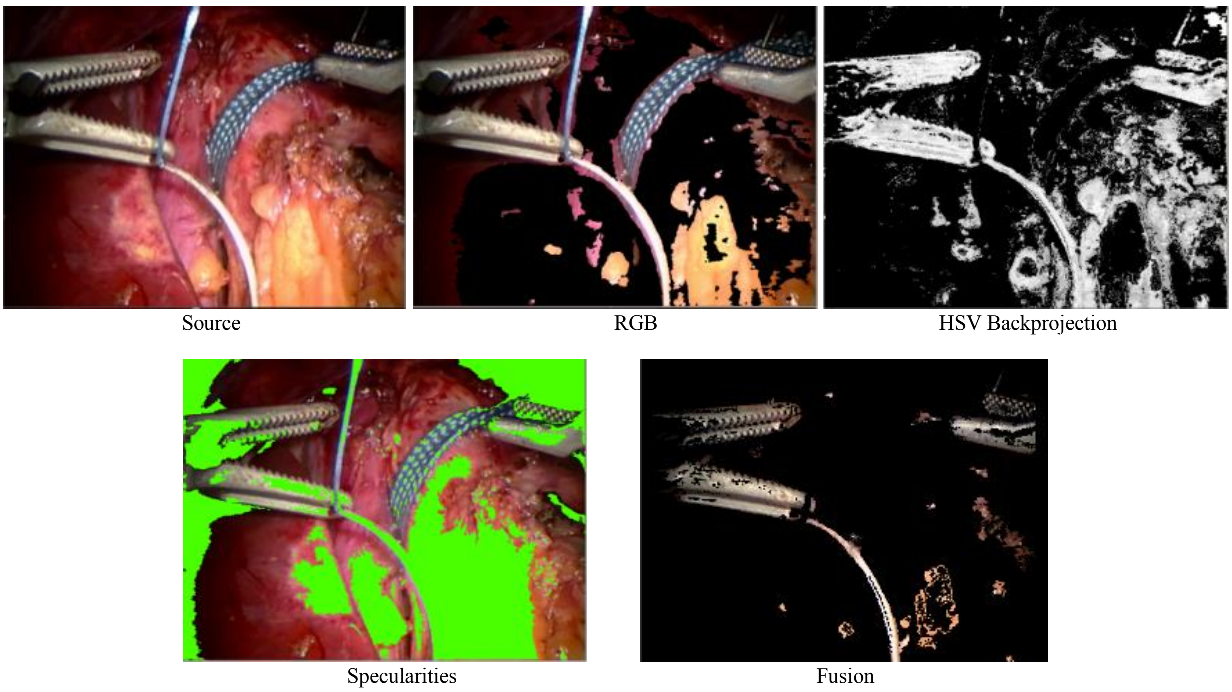

Fig. 2: Visual cues for color segmentation.

2.2 Geometry-based needle segmentation

Geometry-based segmentation is based on the resulting fused image generated by the previous color segmentation. Geometric characteristics of the needle are used to discriminate the elliptical shape of the needle against other structures that could not be excluded before (Fig. 3).

Line detection

The method of Steger [4] was adapted to fit the special requirements for needle detection. It is based on a detection that explicitly models lines and the interaction with corresponding edges based on the lines' surroundings, followed by a scale-space analysis. After the line detection, morphological closing followed by a contours extraction is applied whereas small contours are excluded.

Ellipse fitting

Most of the time, the circular shape of the suturing needle is projected as an elliptical shape onto a 2D plane. Therefore, ellipse fitting with a direct least square approach is the basis the geometry-based segmentation step [5]. The detected ellipses are returned as rotated rectangles and are characterized by the center point, the length of the box corresponding to the major and minor axes, as well as the tilt angle.

Shape analysis

The ellipse validity is verified by using the mass center of the contour which is determined by computing the spatial contour moments. The position of the mass center with respect to the center line of the detected ellipse is now used for shape analysis. Therefore, a box around the center line of the detected ellipse is defined where the size of the box depends on the ellipse parameters. If the mass center is outside this box, the contour is accepted and the fitted ellipse is added to the image.

As a result of the segmentation, the detected needle contour and the corresponding bounding box is returned and serves as input for the tracking.

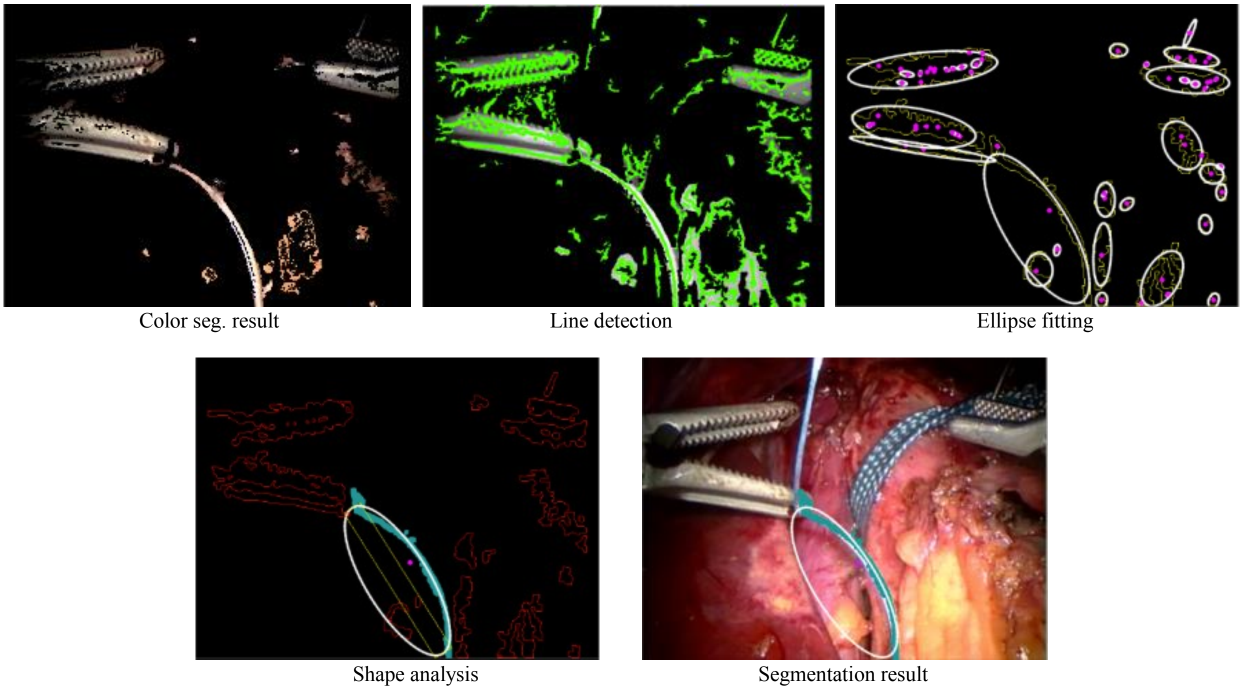

Fig. 3: Geometry-based needle segmentation.

2.3 Needle Tracking

Figure 4 visualizes the overall tracking process. A prerequisite for the tracking is a stable initial segmentation for n subsequent frames as described in the previous section. Based on the initial segmentation, a region of interest (ROI) enclosing the detected needle contour is defined. A reduced segmentation is applied on the ROI which consists of RGB thresholding and histogram backprojection. Afterwards the cues are fused resulting in a smoothed binarized image and an ellipse fitting together with a shape analysis is applied as described in the segmentation section. In case the needle detection fails, a circular Hough transform followed by an ellipse detection is furthermore used to segment the needle contour. If the needle is detected, the ROI is adapted to the current estimation of the needle position. Otherwise the old ROI is adopted for the next frame. In order to improve robustness and reduce false detection results, a complete segmentation is applied to the entire picture every k frames to synchronize segmentation and tracking.

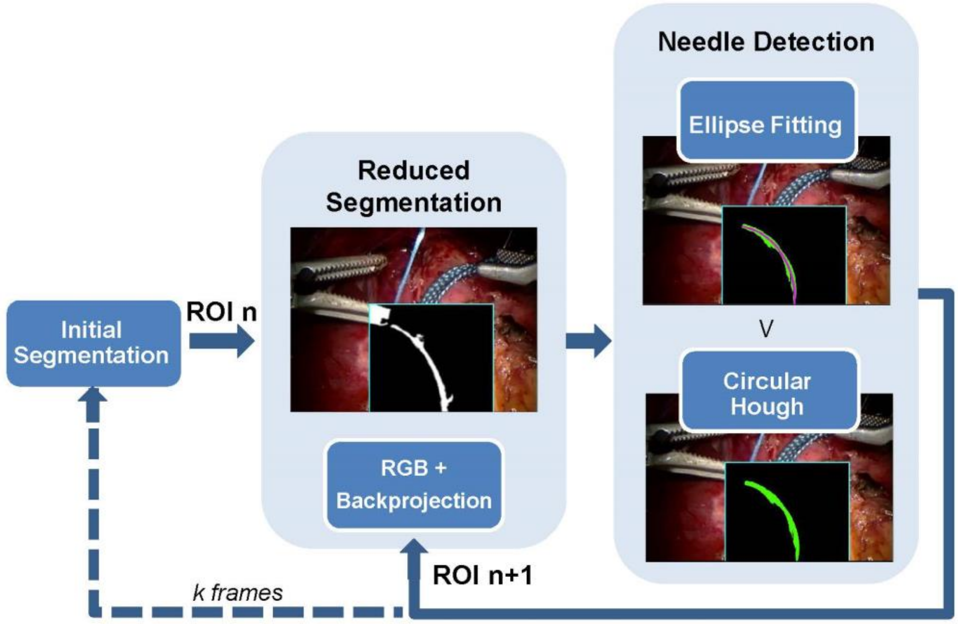

Fig. 4: Needle tracking.

3. RESULTS

The needle segmentation and tracking was evaluated with two different in vivo recordings from da Vinci interventions. Five different suturing sequences including occlusion with partially visible needles and varying lighting conditions were used. For all sequences, the same parameters were taken. Accuracy and robustness was evaluated by comparing the results to manual segmentation.

3.1 Segmentation Results

Color-based segmentation
The color-based segmentation possibly results in an incomplete segmentation of the needle. If less than 45% pixel ratio of segmented needle pixels and the reference segmentation occurs, the needle tracking is unstable. Applying the 45% criterion to the evaluation data led to successful needle segmentation in 92% of the sequence frames.

Geometry-based segmentation
If the color-based segmentation succeeded in isolating suturing needle from the background, the line detection is not considered a critical step. Applying ellipse fitting and shape analysis to remaining regions and contours is aiming at identifying the elliptical suturing needle arch by discarding non-elliptical shapes. Overall, in 49% of the input images the needle contours were detected. The comparatively low detection rate is due to specular highlights, lighting conditions and occlusion that impeded a complete ellipse fitting.

The segmentation was also evaluated on 50 images without a needle in the image. The images from both surgical interventions were chosen to represent a variety of different views including metallic instruments. All in all, 3.5% of the images led to false detection of a suturing needle due to the presence of curved metallic structures, e.g. a coagulation device.

3.2 Tracking Results

Once a robust initial segmentation is guaranteed, a reduced image segmentation on the ROI is applied. The average detection rate increases from 49% to 73% compared to solely segmentation when previous information is taken into account. Furthermore, the classification metrics recall and precision were calculated (Fig. 5). As shown in figure 5, precision is quite high since the method had no problems with false positives. The recall (true positive rate) is lower, especially for sequence 2-4. This is due to the fact that specular highlights, lighting conditions and occlusion strongly impeded the needle detection, especially the ellipse fitting.

Seq	Precision	Recall
1	0.94	0.88
2	1	0.6
3	0.93	0.53
4	1	0.51
5	1	0.88

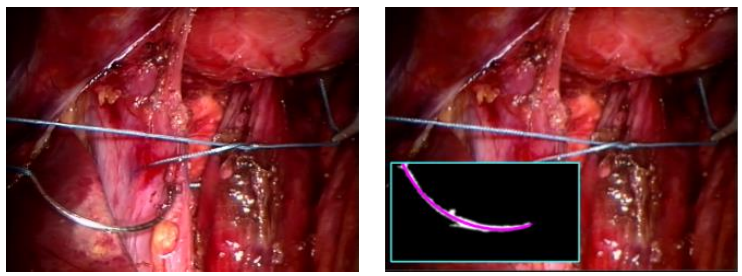

Fig. 5: Left: Precision and Recall score of the method for five sequences. **Right**: Exemplary tracking result.

4. CONCLUSION

In this paper, we presented an approach towards an image-base needle tracking in laparoscopic interventions. The method uses color-based and geometry-based segmentation to detect the needle. Once a stable needle detection is obtained, a region of interest is passed to the tracking component. It is evaluated with in vivo images from da Vinci interventions. The method shows promising results for tracking a markerless needle. Nevertheless the true positive rate of the method can be enhanced in the presence of specular highlights, varying lighting conditions and occlusion that impeded a complete ellipse fitting. Next steps include a more reliable segmentation considering occlusions and overlapping instruments. Furthermore, up to now the orientation is not determined where we also focus on.

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