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SIDF: A Novel Framework for Accurate Surgical Instrument Detection in Laparoscopic Video Frames

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Abstract

Background and Objectives: Identification of surgical instruments in laparoscopic video images has several biomedical applications. While several methods have been proposed for accurate detection of surgical instruments, the accuracy of these methods is still challenged high complexity of the laparoscopic video images. This paper introduces a Surgical Instrument Detection Framework (SIDF) for accurate identification of surgical instruments in complex laparoscopic video frames.

Methods: Based on the Generalized Near-Set Theory, a novel image segmentation algorithm, termed Generalized Near-Set Theory-based Image Segmentation Algorithm (GNSTISA) was developed. According to SIDF, first GNSTISA is executed to segment the laparoscopic images. Next, the segments generated by GNSTISA are filtered based on their color and texture. The remaining segments would then indicate surgical instruments.

Findings: Using the laparoscopic videos of varicocele surgeries obtained from Hasheminezhad Kidney Center, the performance of GNSTISA was compared with previous image segmentation methods. The results showed that GNSTISA outperforms the earlier algorithms in term of accurate segmentation of laparoscopic images. Moreover, the accuracy of SIDF in identifying the surgical instruments was found superior to that of other methods.

Conclusions: SIDF eliminates the limitations of previous image segmentation methods, and can be used for precise identification of surgical instrument detection.

Keywords: Laparoscopy, Surgical instrument detection, Image segmentation, Generalized Near-set Theory

Background and Objectives

Laparoscopy is a relatively new minimally-invasive surgery method, in which, the surgeon rather than looking directly into the inside of the patient's body, uses a camera inserted into the patient's body called “laparoscope” to perform the surgical operation. The laparoscopic video frames can be recorded and processed to yield valuable information. The extracted information can be used in improving the operation room performance, surgical simulations, and robotic surgeries. Simulating a laparoscopic surgery can be used in training surgeons and enhancing their surgical skills [1].

Segmentation of laparoscopic video frames and identifying surgical instruments in each frame allow for extraction of more useful information. For example, time-waste in each laparoscopic surgery can be identified and analyzed using surgical instruments' pattern of usage and motion track. Analysis of laparoscopic time-waste in turn can lead to identification of its causes, thereby helping reduce the potential time-waste, and hence improve the efficiency of resources utilization and shorten the time required for each surgery.

In image segmentation, the pixels are grouped into different homogeneous regions using mathematical algorithms [5]. Several image segmentation algorithms have been introduced [5, 11-15]. While in some methods, images are segmented based on their texture features [11-13, 16], others employ color features for segmentation [17-20]. There are also a number of methods, which combine color and texture features for image analysis [5, 15].

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Greoger *et al.* developed a method for identifying surgical instruments using artificial markers [21]. In this method, an artificial marker (a color strip) with the color different from the colors of all visible tissue cells is used on the distal part of the surgical instrument shaft to help identifying the surgical instruments. While this method helps fast identification of surgical instruments, it has some limitations. For instance, because in many video frames only the tool tip is observed, the artificial markers on the distal part of the instrument (the colored regions of the instrument) become invisible. Moreover, blood and other liquids may cover the instrument, and hide the artificial markers. These limitations render artificial marker detection difficult and oftentimes even impossible.

There are methods attempting to identify surgical instruments focusing on the pixels of instrument edges [2,4] and tool tips [4]. Although edge detection methods can help identify instruments with high precision in the absence of a shadow of surgical instrument, they are error-prone in the presence of an instrument's dark shadow on its neighboring soft tissues [2,4]. Another study introduced a color-based method for surgical instrument detection [3]. Although this method runs fast, it may misdiagnose dark shadows as surgical instruments.

There are several challenges towards laparoscopic instrument detection:

1. Illumination variation: Illumination variation leads to variation of color of metallic surgical instruments. For instance, different pixels of a silver instrument may appear in different colors in a particular image. Moreover, variation in illumination can change the average intensity of an identical object in different images, which challenges the video processing.

2. Complex background: Laparoscopic images include surgical instruments, tissues, and vessels. Each tissue includes a number of asymmetric capillaries. Moreover, the internal cells of a tissue have non-uniform structures that are visible while the tissue is being cut. These issues correct segmentation of the images difficult for texture descriptors. In addition, soft tissue usually changes and moves because of its biological activities, leading to complex backgrounds in the laparoscopic images. Camera motion, on the other hand, adds to background complexity of the laparoscopic images. Hence, background detection based on analyzing the motion patterns of pixels is an error-prone task.

3. Vague instrument boundaries: The shadow of an instrument on the soft tissue may prevent identification of the exact boundaries of the instrument.

4. Invisible tool tip: The shape of the instrument tip can help discriminate different surgical instruments. However, since the instrument tip is not visible inside the tissue, the shape of the instrument tip alone cannot always be used for instrument detection.

These challenges limit the effectiveness of approaches like background modeling [22-23], edge detection [24-25], color and/or texture image segmentation [3, 5, 26, 27], and artificial marker-based segmentation [21] in instrument detection. Therefore, there is a need to further improving the previously developed methods of surgical instrument detection in order to eliminate these limitations. This paper proposes a two-stage Surgical Instrument Detection Framework (SIDF). For this purpose, first, a new image segmentation algorithm called Generalized Near-Set Theory-based Image Segmentation Algorithm (GNSTISA) is executed. The segments generated by GNSTISA are then filtered based on their color and texture and the remaining segments will indicate surgical instruments.

Methods

Image Resource

Laparoscopic videos of varicocelectomy surgeries were obtained from correct segmentation of the images Hasheminejad Kidney Center (Tehran, Iran) in [2010-2011]. The proposed method was evaluated using the video frames. SIDF was applied on some complex video frames of laparoscopic surgery.

Generalized Near-Set Theory-based Image Segmentation Algorithm (GNSTISA)

GNSTISA is an image segmentation algorithm developed based on the Generalized Near-Set Theory (GNST). The GNST has been described elsewhere [28-29], and a brief description of it is provided in appendix the Additional File 1. The main stages of the GNSTISA method are displayed Figure 1. GNSTISA calls two different image segmentation algorithms with different feature sets. One algorithm uses color descriptors as input, and the other deals with a combination of texture and edge descriptors. Color descriptors are defined in the L*U*V* color space because of their reportedly high performance in this space in clustering pixels [15].

The first stage of GNSTISA produces too many small segments that should be merged to produce a few large segments, representative of the objects.

In our method, two overlapping segments can be merged if their features have similar values. The similarity of two segments is measured based on GNST. GNST provides a framework for segmenting images based on multiple feature sets, which allows using several features to describe objects of a set, rather than using only a single feature as in traditional image segmentation methods.

If the generated segments satisfy the proposed merging conditions defined by GNST (Additional File 1), then they can be merged. GNST approximates each set (of pixels) considering its 'near' objects (objects having similar features [28-29]).

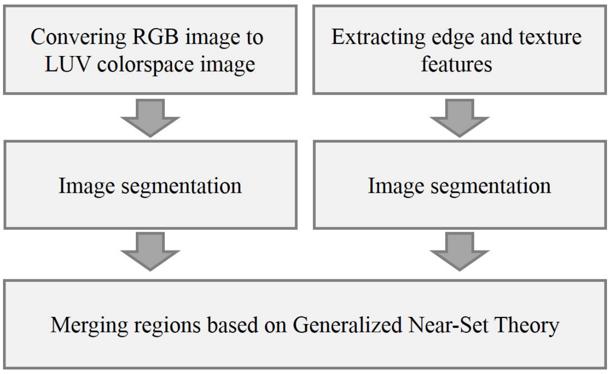

Figure 1 The main stages of GNSTISA for segmenting laparoscopic images

Surgical Instrument Detection Framework (SIDF)

SIDF includes two main stages (Figure 2):

- Segmentation images using the GNSTIS algorithm: each video frame is segmented by the GNSTIS algorithm and the output will be used in the next stage.
- Filtration of the image segments based on their color and texture: if the color and texture of a segment differ from those of the surgical instruments, they will be filtered. Finally, a bi-color image (black and white) is produced in which the white region indicates surgical instrument.

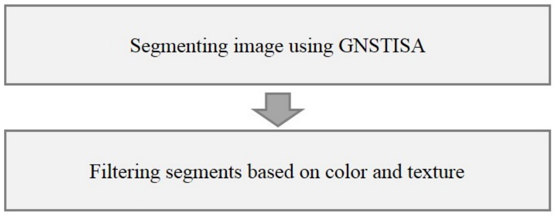

Figure 2 The main steps of SIDF for surgical instrument detection in laparoscopic images

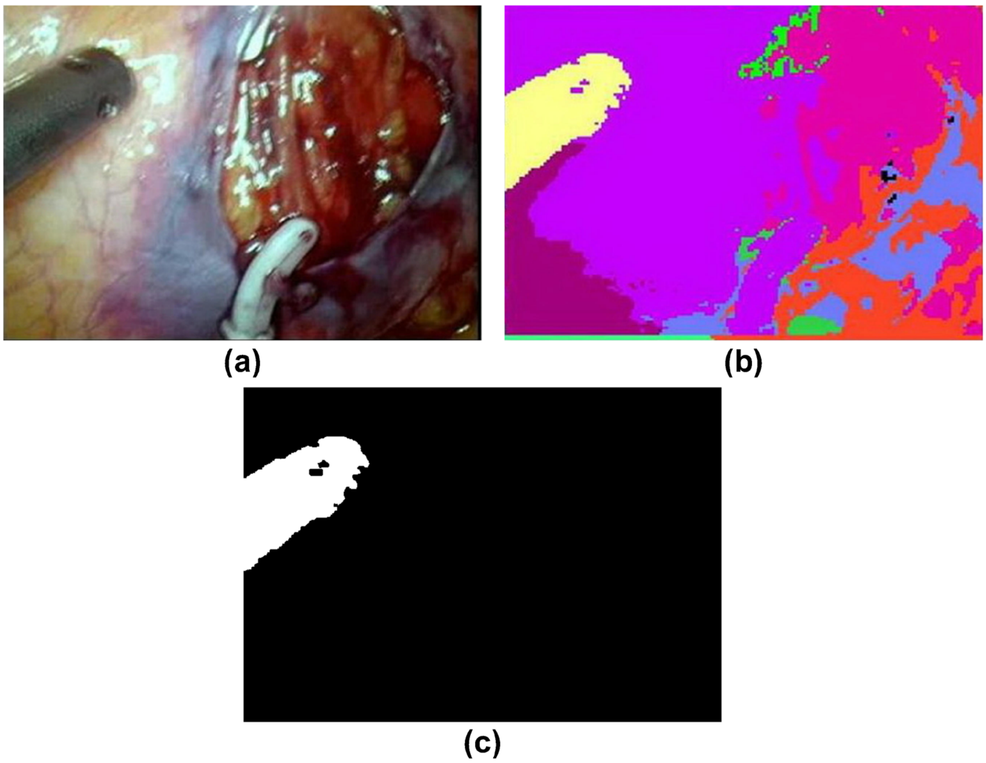

Figure 3 An example of executing SIDF on a sample laparoscopic video frame: (a) the original image of a sample video frame, (b) segments obtained from the 1st stage of SIDF on the sample video frame, (c) surgical instrument regions identified by 2nd stage of SIDF on the segments.

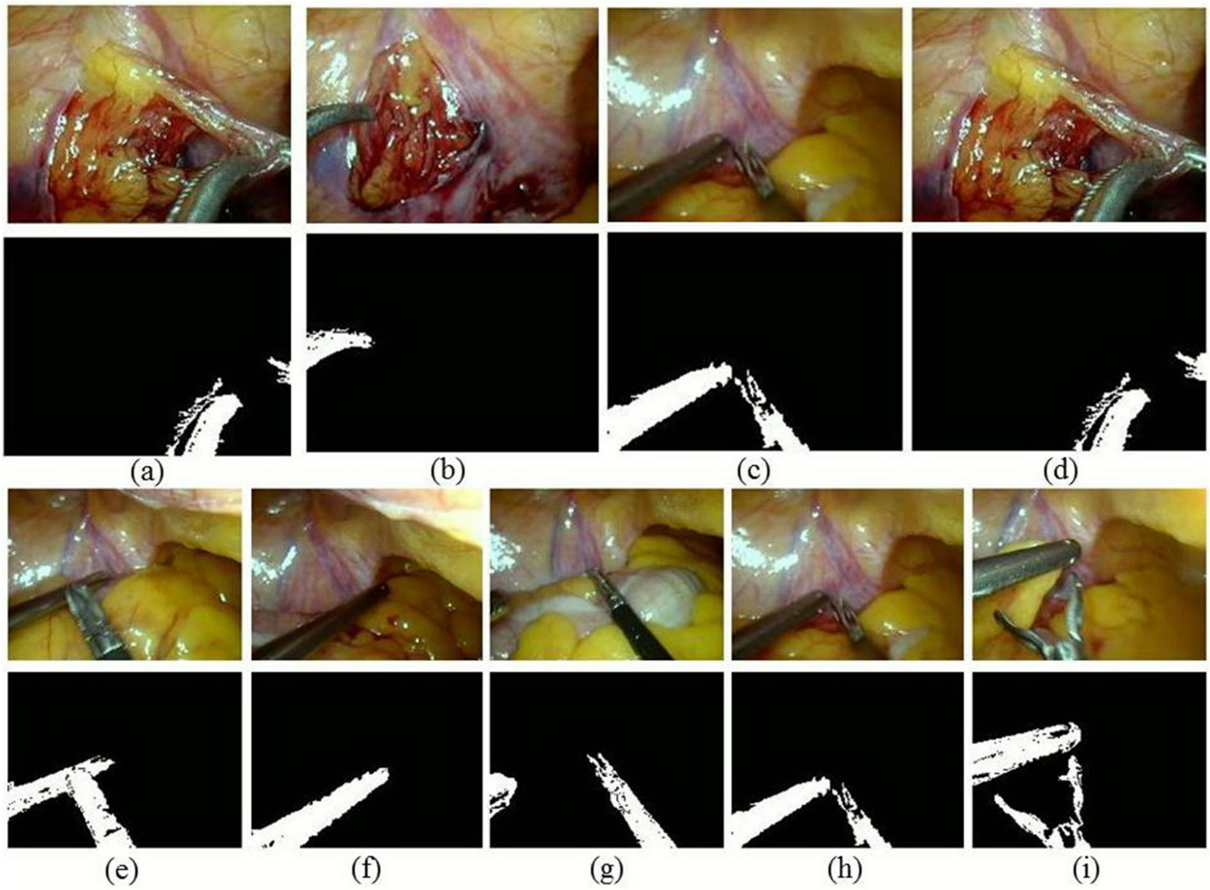

Figure 3 The laparoscopic video frames and their corresponding SIDF outputs

Table 1 Comparing the performance of GNSTISA with other image segmentation algorithms in laparoscopic video frames

Algorithm	**Q(S)**		
	Min	**Max**	**Mean**
Seeded region growing algorithm [32]	0.0363	0.0472	0.0408
Color and texture integrating algorithm [14]	0.1020	0.1155	0.1083
Hill climbing algorithm [33]	0.1625	0.1842	0.1708
GNSTISA (This study)	0.0158	0.0199	0.0178

Table 2 Comparison of the performance of SIDF with other surgical instrument detection methods

Method	Precision of laparoscopic instrument detection (%)
Cano et al. [2]	87.3
Doignon et al. [3]	83.8
Voros et al. [4]	86.7
SIDF (This study)	94.3

As an example, consider the sample laparoscopic video frame in Figure 3(a). After executing the first stage of SIDF, the video frame is segmented as illustrated in Figure 3(b) (different segments are shown in different colors for better visualization). The segmented image is then input to the second stage of SIDF. The output is illustrated in Figure 3(c); the white region represents the surgical instrument.

Performance Evaluation

Evaluating the performance of the GNSTIS algorithm

We compared the performance of GNSTISA with other segmentation algorithms. For this purpose, the quality of image segmentation had to be measured. There is no established standard for quantized evaluation of image segmentation results [30]. However, Borsotti *et al.* [31] proposed a criterion called Q(S) for image segmentation evaluation, which was used in previous image segmentation algorithms [30-31]. For the ease of comparison, we used the same method in this study to evaluate the quality of image segmentation based on the proposed algorithm. Q(S) is formulated as follows [30-31]:

$$Precision = \frac{TP}{N} \quad (1)$$

where *TP* denotes the number of correctly identified surgical instruments, and *N* represents the total number of visible surgical instruments in the examined laparoscopic video frames.

Evaluating the performance of surgical instrument detection

The performance of surgical instrument detection was evaluated based on its precision. The precision was calculated as below:

$$Q(S) = \frac{1}{10000N\times M}\sqrt{R}\sum_{i=1}^{R}\left(\frac{e_i^2}{1+logA_i}+\left(\frac{R(A_i)}{A_i}\right)^2\right) \quad (2)$$

where, *S* denotes the segmented image, M and N refer to the image dimensions, *R* denotes the number of identified regions in the segmented image, $A_{i,}$ represents the size of the region *I* in pixels, $R(A_i)$ is the number of regions with area equal to *Ai*, and $e_{i,}$ is the sum of the Euclidean distance between the features of the pixels in a cluster and the representatives of that cluster. A smaller value of *Q(S)* indicates a better segmentation result.

Results

The laparoscopic images shown in Figure 4 were segmented using the seeded region growing algorithm [32], algorithms integrating color and texture features [14], hill climbing algorithm [33], as well as GNSTISA, and the Q(S) corresponding to each algorithm was calculated. Table 1 compares the Q(S) values calculated from the GNSTISA and other algorithms. As seen, GNSTISA outperforms the previously developed algorithms in terms of accurate segmentation of laparoscopic images.

To examine the performance of SIDF in surgical instrument detection, three hundred laparoscopic video frames were randomly selected from the laparoscopic varicocelectomy videos, segmented, and subjected to surgical instrument detection analysis. Table 2 compares the performance of SIDF with other proposed methods. As shown, the SIDF outperformed other methods in accurate identification of the surgical instrument.

Discussion

Surgical instrument identification in laparoscopic video frames offers four useful applications: 1) feature extraction for virtual reality and surgical simulation purposes, 2) image-guided surgery using surgical instrument information, 3) automatic detection of surgical instruments, aiding in robotic surgeries, and 4) improving operation room performance.

Nevertheless, segmentation of laparoscopic images for instrument detection is a challenging task because of the complexity of such images. At the same time, presence of surgical instruments in the images adds to the complexity of the image segmentation process because of these images' color, texture, and in some cases, boundary variations. In this paper, a framework termed SIDF is proposed for detection of surgical instruments in laparoscopic images; which runs a novel image segmentation algorithm (GNSTISA), capable of combining the results of multiple segmentation methods to improve the quality of segments.

The results of executing the SIDF on a sample of complex images revealed that it outperforms the previously proposed methods.

Previous surgical instrument detection methods [2, 4] could not precisely detect surgical instruments in the images shown in Figure 4(a-b), (d), and (i), possibly due to the boundary vagueness of surgical instruments in these images (the third challenge of laparoscopic instrument detection mentioned before). Moreover, the method proposed by Doignon *et al.* [3] had a relatively low performance in some images for using only color descriptors in identification of surgical instruments, which is not suitable in varied illumination conditions. On the other hand, this method cannot discriminate between instrument regions and dark shadows; hence, it is not accurate enough to detect surgical instruments in the images shown in Figure 4(a-i).

Although the images displayed in Figure 4 are complex, our proposed SIDF, is capable of identifying all surgical instruments with higher accuracy as compared with the previously developed methods.

In the future studies, the performance of GNSTISA can be evaluated on general applications such as segmenting face images, outdoor scene images, and etc. GNSTISA can combine two image segmentation algorithms, and improve their segmentation performances. Therefore, one possible extension of this work is using the combination of fast segmentation methods in the first stage of GNSTISA algorithm. Another possible extension of this study is the evaluation of GNSTISA performance using motion descriptors in the segmentation process, which would enable a dynamic tracking of the instrument during the surgery.

Conclusions

Accurate analysis of laparoscopic videos is a challenging task due to the complexity of the images. In this study, based on the Generalized Near-Set Theory, we developed a novel image segmentation algorithm (GNSTISA) with a higher performance as compared with the earlier algorithms. We also proposed a novel Surgical Instrument Detection Framework (SIDF), which by allowing filtration of the segmented images obtained from GNSTISA, accurately identifies the surgical instrument. Examination of SIDF on 300 laparoscopic video frames demonstrated that it offers considerably higher accuracy compared to the previously developed frameworks. Hence, our results recommend preferred use of SIDF among parallel methods for practical applications.

Abbreviations

(GNST): generalized near-set theory; (SIDF): surgical instrument detection framework; (GNSTISA): generalized near-set theory-based image segmentation algorithm

Competing interests

The authors declare that there are no conflicts of interest.

Authors' Contributions

MMS and PS jointly designed the study. TKH has the major contribution to developing the GNSTISA and SIDF, analyzing the data, and drafting and revising the manuscript. MMS contributed to preparing and revising of the manuscript. PS determined the settings and contributed to interpretation of the results. All authors read and approved the final manuscript.

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