Automatic Real-Time Smoke Removal in Endoscopic Surgery

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1. Introduction

The visibility of images and videos plays an important role in computer aided endoscopic surgery that relies heavily on real-time computer vision applications such as tracking and navigation systems. However, surgical smoke resulting from the use of electrosurgical unit (ESU) often decreases the visibility, thus degrading the system performance. To guarantee the efficacy of tracking and navigation systems under all viewing conditions during the surgery, an effective real-time processing which restores the smoke-degraded degraded visibility of features is critical in ensuring the system robustness. This paper proposes a fast, automatic single-image smoke removal approach for visibility restoration of smoky views in endoscopic surgery. The time efficiency of the approach makes it suitable for real-time applications.

2. Related Work

Surgical smoke removal in endoscopic surgery is a field which has hardly been explored in the literature. As the physical properties of smoke, fog, and haze are similar, prior work on fog and haze removal is considered to be of high relevance.

Enhancement-based techniques suffer from poor color fidelity [1] and loss of low spatial frequencies [2]. Restoration-based technique, which gives better results and has received a considerable amount of research attention, is based on physics-based smoke model. The distance map is represented by *d(x,y)*. Koschmieder's law [3]–[5] gives the smoke model as

$$\boxed{I(x,y) = R(x,y)e^{-kd(x,y)} + V(x,y)} \quad (1)$$

I(x,y) is the original smoky image, *R(x,y)* is the image without smoke, *k* is the extinction coefficient, and *V(x,y)* is the airlight, or atmospheric veil, which is formulated as

$$\boxed{V(x,y) = I_s(x,y)(1 - e^{-kd(x,y)})} \quad (2)$$

Is(x,y) is the sky intensity. As smoke is a function of the distance map *d(x, y)*, most restoration-based techniques estimate the depth before restoration. As depth can be obtained via stereoscopy, some algorithms take multiple images as input [3], [6]. However, the requirement on the number of images restrict the applications [1].

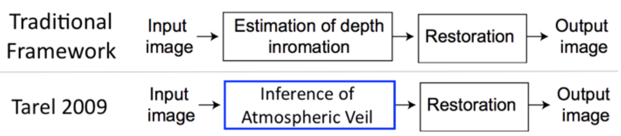

Fig. 1. Smoke removal frameworks.

Single-image restoration spans a wide range of applications is, nonetheless, challenging. Most existing algorithms for smoke removal are not efficient enough to meet the speed requirement of real-time applications. Tarel [7] presented a fast fog removal method which bypasses the estimation of depth by considering an alternative representation of Eq. (1)., which is

$$\boxed{I(x,y) = R(x,y)\left(1 - \frac{V(x,y)}{I_s}\right) + V(x,y)} \quad (3)$$

By assuming the sky intensity and inferring the airlight *V(x,y)*, the image without smoke R(x,y) can be restored without depth estimation. Different smoke removal frameworks are shown in Fig. 1. Tarel's algorithm is much faster than [8]–[10] with its time complexity being a linear function of the number of pixels in the image. Although Tarel's method is fast, it requires adjustment of many parameters and suffers from compromised restoration quality with the presence of discontinuities in the image depth map [1].

3. Methodology

3.1 Data Source

The data source is the actual laparoscopic surgery videos recorded by Doctor Jiang Chen, Renji Hospital, Shanghai Jiao Tong University School of Medicine.

3.2 Assumption & Algorithm

It is noted that studies on fog removal mostly focus on images of natural outdoor scenes where the range of distance is large while the range of distance is much smaller in endoscopic views. The study builds on the basis of Tarel's approach and introduces modifications suited to smoke removal in endoscopic views.

The key of the algorithm is the inference of airlight, which is achieved under several assumptions. Airlight is assumed to be a percentage between the local standard deviation and the local mean of the whiteness. The depth map is assumed to be mostly smooth except for edges.

Color balance is first conducted to ensure that the smoke is pure white, and the sky intensity *Is(x,y)* can be set to (1,1,1). The image is than normalized to [0,1]. The inference of airlight *V(x,y)* is formulated by Tarel and Hautiere [7] as an optimization problem

$$\boxed{\underset{V}{argmax} \int_{(x,y)} V(x,y) - \lambda\varphi(\|\nabla V(x,y)\|^2)} \quad (4)$$

with the constraint

$$\boxed{0 \le V(x,y) \le W(x,y)} \quad (5)$$

where λ controls the smoothness of the solution and φ is an increasing concave function. *W(x,y)* is the whiteness of the image *I(x,y)*, defined as

$$\boxed{W(x,y) = \min\,(I(x,y))} \quad (6)$$

As the optimization is computationally intensive, an approximation with linear operations is performed to obtain the solution. The study uses bilateral filter instead of median filter proposed by Tarel for better edge preserving. The linear operations for airlight inference are

$$\boxed{A(x,y) = bilateralFilter_{(s,s)}W(x,y)} \quad (7)$$

$$\boxed{B = A(x,y) - bilateralFilter_{(s,s)}(|W - A|)(x,y)} \quad (8)$$

$$\boxed{V(x,y) = \max\left(\min\left(pB(x,y), W(x,y)\right), 0\right)} \quad (9)$$

The image is then restored by

$$\boxed{R(x,y) = \frac{I(x,y) - V(x,y)}{1 - \frac{V(x,y)}{I_s}}} \quad (10)$$

Finally, smoothing and tone mapping are performed for contrast enhancement and color restoration.

The algorithm is realized in Python 3 with OpenCV 3. The time efficiency of the smoke removal algorithm is O(MN), where M and N are the height and width (in number of pixels) of the input image.

3.3 Performance Metrics

To analyze the performance quantitatively, the method proposed by [5] is used. The three metrics are: e, the rate of new visible edges; Σ, the percentage of pixels that become completely black or white; and r, the mean ratio of the gradients at visible edges.

4. Results

4.1 Quantitative Results

Table 1. shows the quantitative results of four different images (a), (b), (c), (d) with the performance metrics described in section 3.3.

Table 1 Quantitative results of images (a), (b), (c), (d).

Metric	*Img(a)*	*Img(b)*	*Img(c)*	*Img(d)*	*Avg*
e	0.06773	0.02114	0.18181	0.16412	0.10870
Σ (%)	0.00473	0.00820	0.00174	0.00371	0.00459
r	1.0809	1.0408	1.1903	1.1465	1.11463

With e positive across all images, the restoration has been shown to increase the number of visible edges. As Σ are very small, the saturation percentage is reasonably low and the contrast enhancement is not too strong. Lastly, r entails the average increase of contrast on visible edges.

Table 2. shows the quantitative results of He's and Tarel's algorithms averaged over four images [7]. There is a trade-off between preserving/obtaining visible edges and enhancing contrast is. While He's approach does better obtaining/preserving visible edges, the algorithm enhances the contrast at visible edges more and runs much faster.

Table 2 Quantitative comparison of different approaches.

Metric	*He*	*Tarel*
e	0.0525	0.0190
Σ (%)	0.0025	0.0000
r	1.4550	1.9625

4.2 Qualitative Results

Fig. 2. Shows the qualitative results on images (a), (b), (c), (d) where the upper row shows the original and the lower row shows the restored images. It is shown that the compromised visibility and lowered contrast due to surgical smoke are restored with slight color distortion.

5. Conclusion

5.1 Research Plan

The next steps of the study include parameter tuning and conditional restoration.

As the parameters including assumed smallest white object size s, percentage of restoration p, factor for gamma correction g, and window size for adapted filtering w affect the restoration result, it will be best to finetune the parameters to optimize the restoration quality. Metric learning is proposed for this purpose.

Additionally, it is noted that the performance might be improved if the restoration is conditioned on the presence of smoke instead of unconditionally. The implementation of an efficient smoke detection function is required to achieve conditional restoration.

Future study may explore metric learning and conditional restoration with smoke detection.

5.2 Summary

Real-time smoke removal is critical to ensuring the robustness of tracking and navigation systems [7] for computer aided surgery while a research gap remains. The paper proposes an efficient approach for real-time visibility restoration in smoky endoscopic views with demonstrated improvement in visibility restoration. The study may benefit real-time medical computer vision applications requiring clear features in the view.

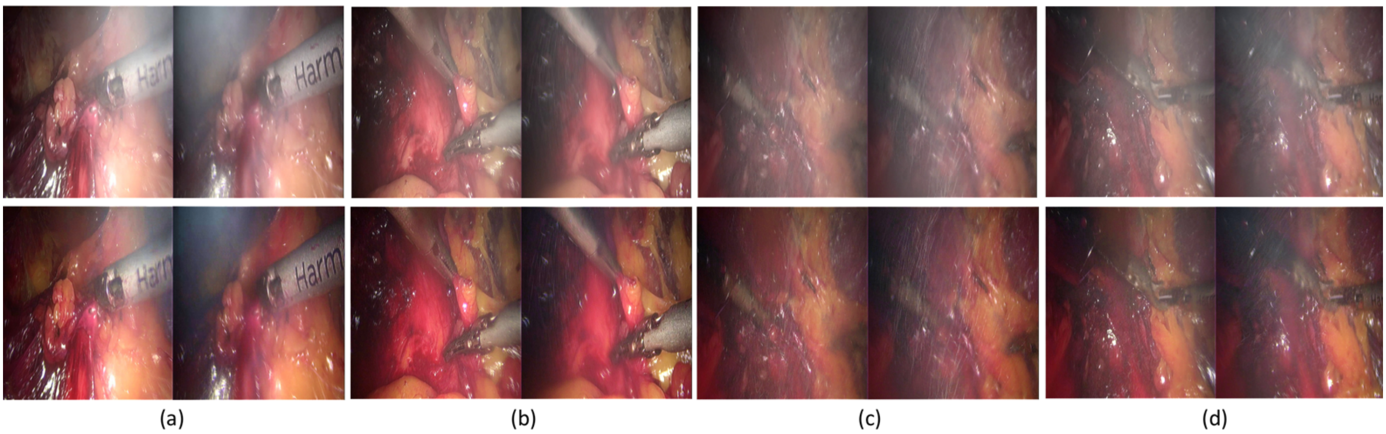

Fig. 2. Qualitative results of images (a), (b), (c), (d).

Acknowledgements

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