

Removal of smoke effects in laparoscopic surgery via adversarial neural network and the dark channel prior

Eliminación de los efectos de humo en cirugía laparoscópica usando redes antagónicas generativas y el principio del canal oscuro

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Abstract

Background: In laparoscopic surgery, image quality can be severely degraded by surgical smoke caused by the use of tissue dissection tools that reduce the visibility of the observed organs and tissues. **Objective:** Improve visibility in laparoscopic surgery by combining image processing techniques based on classical methods and artificial intelligence. **Method:** Development of a hybrid approach to eliminating the effects of surgical smoke, based on the combination of the dark channel prior (DCP) method and a pixel-to-pixel neural network architecture known as a generative adversarial network (GAN). **Results:** Experimental results have shown that the proposed method achieves better performance than individual DCP and GAN results in terms of restoration quality, obtaining (according to PSNR and SSIM index metrics) better results than some related state-of-the-art methods. **Conclusions:** The proposed approach decreases the risks and time of laparoscopic surgery because once the network is trained, the system can improve real-time visibility.

Keywords: Laparoscopy. Image improvement. Haze removal. Image processing. Generative adversarial network.

Resumen

Antecedentes: Durante la cirugía laparoscópica, la calidad de la imagen puede verse gravemente degradada por el humo quirúrgico causado por el uso de herramientas de disección de tejidos que reducen la visibilidad de los órganos y tejidos. **Objetivo:** Mejorar la visibilidad en cirugía laparoscópica mediante la combinación de técnicas de procesamiento de imágenes basadas en técnicas clásicas e inteligencia artificial. **Método:** Desarrollo de un enfoque híbrido para la eliminación de los efectos del humo quirúrgico, basado en la combinación del método del principio del canal oscuro (DCP, dark channel prior) y una arquitectura de red neuronal píxel a píxel conocida como red antagónica generativa (GAN, generative adversarial network). **Resultados:** Los resultados experimentales han demostrado que el método propuesto logra un mejor rendimiento que los resultados individuales de DCP y GAN en cuanto a calidad de la restauración, obteniendo (según las métricas de la proporción máxima de señal a ruido [PSNR, Peak Signal-to-Noise Ratio] y el índice de similitud estructural [SSIM, Structural Similarity Index]) mejores resultados que otros métodos relacionados. **Conclusiones:** El enfoque propuesto disminuye los riesgos y el tiempo de la cirugía laparoscópica, ya que una vez que la red está correctamente entrenada, el sistema puede mejorar la visibilidad en tiempo real.

Palabras clave: Laparoscopia. Eliminación de humo. Procesamiento de imágenes. Red antagónica generativa.

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Introduction

Laparoscopic surgery consists of the insertion of a camera and surgical devices through small incisions. It has largely replaced traditional surgery in various surgical fields, such as abdominal surgery, gynecology, thoracic surgery, etc., because it has a lower incidence of infections and a faster recovery, and generally leaves fewer sequelae than traditional surgery. In this type of procedure, cauterization is performed on the tissues, which causes water vapor and carbon monoxide that diminish the visibility of the cameras used. This lack of visibility increases surgery time and even the likelihood of errors made by the surgeon, which can lead to negative consequences for the patient's health¹. Commonly, the smoke removal process is performed with medical instruments, but this is costly and impractical, so another option is required to solve the problem. The aforementioned has motivated the development of research in digital image processing, which has focused on the search for methods to reduce the effects of smoke and, therefore, increase visibility.

One of the classic techniques most commonly used for this purpose is based on the atmospheric scattering model, in which the transmission map (which contains information about smoke density) and the light components in a given image are estimated². For example, Wang, et al.¹ propose a technique based on the physical model of smoke scattering, similar to the model used in image processing to eliminate haze effects (*dehazing*), in which the smoke level is determined considering the fact that low contrast and low inter-channel differences are present in the pixels containing smoke. Based on this observation, a cost function is defined and solved using a Lagrangian method. Kotwal, et al.³ formulate the question of haze and smoke removal in laparoscopic images as a Bayesian inference problem, in which a probabilistic system is used with models of the images without haze, as well as a transmission map indicating color attenuation in the presence of smoke. Gu, et al.⁴ implement a digital system based on the dark channel prior (DCP), where it is observed that, statistically, outdoor haze-free images contain some pixels with very low intensity in at least one of the color channels.

Many problems in image, graphic and vision processing require the conversion of an input image into a given output image. Until a couple of years ago, as mentioned above, most of the research was done using "engineering" methods, i.e., the researcher analyzed and looked for patterns on which they designed an

explicit algorithm. Today, with new advances in machine learning, which is a part of artificial intelligence and deals with models that improve with experience, the situation has changed radically. Now, thanks mainly to deep learning based on convolutional neural networks (CNN) that are able to find patterns and abstractions autonomously, the researcher's task is focused on adapting or developing and adjusting a machine learning model. Generative adversarial networks (GANs) proposed in 2014 are formed by two neural networks and are a general purpose solution that has obtained good results in a wide variety of applications requiring image-to-image mapping, being currently the leading technology in many of them⁵⁻⁹. GANs consist of two main parts: a neural network that acts as a generating function, in which an output image with certain changes is generated from an input image, and a discriminating function that evaluates the generated image with a real image in order to classify it as real or false. The basic idea of GANs is to generate images that are so close to the original that the discriminator cannot find any difference. Isola, et al.⁵ demonstrate that this approach is effective for synthesizing images from label maps, reconstructing objects from edge maps, and colorizing images originally in grayscale. Recent work has proposed deep learning architectures to reduce the effect of smoke on laparoscopic images^{10,11}. Chen, et al.¹² propose the use of GANs for unsupervised learning and smoke removal in images. In this paper we present the results of applying a GAN and also propose a hybrid method that combines an image processing technique with a GAN. An example of the architecture proposed here is shown in Figure 1, where the DCP is used as a preprocessing stage under the hypothesis of the reduction in the complexity of the patterns present in the images that subsequently enter a GAN architecture.

The experiments were performed on a data set with laparoscopy images to which the smoke effect was artificially generated using video editing software. According to the metrics used to evaluate the proposed methods, the use of GAN to reduce the smoke effect improves image reconstruction over the DCP and dispersion model-based approach.

This paper is structured as follows: section "II" (theoretical framework) presents the theoretical and conceptual foundations used for the implementation of the network, as well as the metrics for the evaluation of the results; section "III" (proposed method) explains the configurations used in the design of the experiment; section "IV" (results) presents the results obtained, as

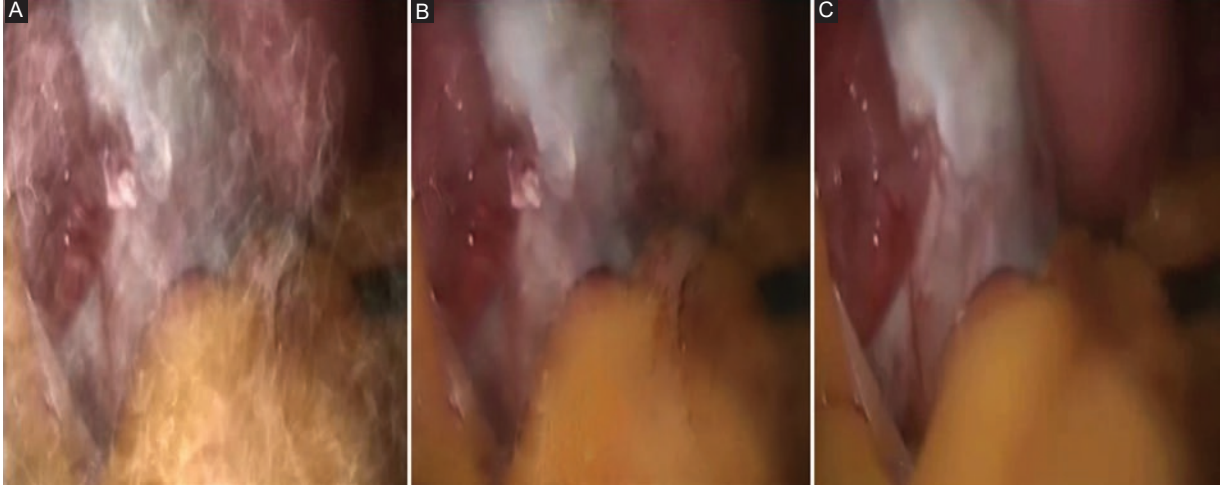


Figure 1. Performance of the DCP + GAN model in a laparoscopic surgical image. **A:** input images with synthetic CO_2 smoke. **B:** our result with DCP + GAN. **C:** ground-truth.

well as the comparative tables with respect to related works; and finally a discussion, conclusions and a perspective for future research are included.

Theoretical framework

This section presents the theoretical foundations necessary for the implementation of the proposed methodology.

ATMOSPHERIC DISPERSION MODEL

Atmospheric degradation is a physical phenomenon caused by particles in the atmospheric medium that absorb and scatter light¹³. This degradation can be expressed, using the dichromatic model¹⁴, as:

$$I(x,y) = J(x,y)t(x,y) + A(1-t(x,y))$$

where $I(x,y)$ is the intensity of the color image at each pixel (x,y) with the presence of haze, $J(x,y)$ is the intensity of the RGB image in each pixel (x,y) without degradation, A is the normalized matrix of the atmospheric light component in each image channel and $t(x,y)$ represents the transmission map in a homogeneous atmosphere, modeled by:

$$t(x,y) = e^{-\beta d(x,y)}, 0 < t(x,y) < 1,$$

where β is the scattering coefficient, that mainly depends on the size of the scattering particle¹⁴ and $d(x,y)$ represents the distance from the camera to the scene at the pixel position (x,y) .

Using the dichromatic model, it is possible to obtain the image without the haze effects $J(x,y)$ as long as an accurate estimate of $t(x,y)$ and A ¹³ can be obtained.

DARK CHANNEL

The dark channel I^{dark} for each pixel is defined as follows:

$$I^{dark}(x,y) = \min_{c \in \{RGB\}} \left(\min_{z \in \Omega\{x,y\}} \frac{I^c(z)}{A^c} \right)$$

where $\Omega\{x,y\}$ is a generally square kernel centered at position (x,y) (using a square kernel has no motivation other than to minimize the most the time required for processing), $I^c(z)$ are the image elements at positions $z \in \Omega\{x,y\}$, represent each image in the respective RGB channels, and constitute the value of each of the c components.

The DCP is based on the observation that, in haze-free images, at least one color channel has a very low intensity in some pixels. In other words, the intensity in a section Ω of the image should have a very low value in some channel if there is no haze between the camera and the captured object. This is defined as the statistical relationship between the dark channel and haze-free regions, where it is satisfied:

$$I^{dark}(x,y) \rightarrow 0$$

The relationship between I^{dark} and t is expressed as:

$$t(x,y) = 1 - \omega I^{dark}(x,y)$$

where $0 < \omega < 1$ represents the restoration level. According to He, et al.¹⁵, $\omega = 0.95$, arguing that this value produces a better appearance in restored images. Alternatively, atmospheric light can be estimated by the equation:

$$A_c = \max \sum_{c=1}^3 \left(\arg \max_{(x,y) \in 0.1\%} (h, \omega) (I^{dark}(x, y)) \right)$$

where h is the height and ω is the width of the image.

GENERATIVE ADVERSARIAL NETWORKS

GANs, presented in 2014 by Goodfellow, et al.¹⁶, are a type of unsupervised learning artificial intelligence method, implemented by a system of two mutually competing neural networks, and a generator (G) that is responsible for generating a fake image from the training of many original images, which learns the fundamental characteristics of a particular type of image; for example, if this stage is trained with many different faces, it will have the ability to generate fake faces with real characteristics. In a second stage, a discriminator (D) is connected, which aims to identify whether an image is real or fake. As the two stages are connected in an iterative process, job G is to generate fake images with features so realistic that it manages to “fool” stage D, at which point the GAN is considered to be trained and only stage G is used in the application. Both the G and D stages are implemented using convolutional layers. In the case of G, convolutional operations are performed to make a dimensionality reduction in the images and then an inverse or deconvolutional operation, until an image of equal dimensions to the input image is generated. Stage D, on the contrary, uses convolutional operations up to the point of having a binary classifier that decides whether the generated image is real (a value of 1 is assigned) or false (a value of 0 is assigned).

Convolutional layers

Convolutional operations on images are inspired by the visual cortex of the human eye, where some cells specialize in detecting particular shapes, such as lines and edges. Along the hierarchy of the cortex, the complexity of stimuli increases. Similarly, convolutional layers connected in a hierarchy allow the first few layers to detect simple image features and, as the layers

increase, higher levels of abstraction are achieved. This quality gives convolutional neural networks the ability to “see” and identify objects. Specifically, each neuron in a feature map is connected to a region of neighboring neurons in the previous layer. The new feature map can be obtained by convolving the input and then applying an activation function.

RECTIFIED LINEAR UNIT

The rectified linear unit (ReLU) is one of the most noticeable unsaturated activation functions, which is defined as:

$$a_{i,j,k} = \max(z_{i,j,k}, 0)$$

where $z_{(i,j,k)}$ is the input of the activation function at location (i,j) in channel k -th. ReLU is a piecewise linear function that prunes the negative part to zero and retains the positive part. The simple $\max(\cdot)$ operation of ReLU allows it to compute much faster than sigmoid or $\tanh(\cdot)$ activation functions, and it also induces sparsity in the hidden units and allows the network to easily obtain sparse representations. It has been shown that deep networks can be efficiently trained using ReLU¹⁷.

CONDITIONAL GENERATIVE ADVERSARIAL NETWORKS

GANs are generative models that learn a mapping from a random noise vector z to an output image y , $G: z \rightarrow y$. Conversely, conditional generative adversarial networks (cGAN) learn from the input image x and the random noise vector z^5 , i.e., $G: x, z \rightarrow y$. This type of network is widely used in methods that require image-to-image translation.

Method

This section describes the methodology used to obtain the data and implement the proposed algorithm.

Obtaining the database

The images used in this work were obtained from videos from different public repositories, as well as from videos provided by a group of physicians specializing in laparoscopic surgery. A comparative video of the results of the proposed methods can be seen in a real surgical video at <https://www.youtube>.

com/watch?v=QvUKcHonCHw&feature=youtu.be. From the available videos, 6000 representative images of different levels of smoke involvement were obtained. To generate the input data, smoke was artificially simulated, using the open source graphics processing software Blender, forming input images with dimensions of 512×512 pixels.

Metrics

To have an insight into the performance of the proposed method in this work, the results are evaluated by employing metrics widely used in the literature: the peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM). These concepts are briefly explained below:

- PSNR is a quantitative measure of the quality of a reconstruction¹⁸. It is widely used in imaging. To define the PSNR metric, it is necessary to define the mean squared error (MSE), which, for two monochrome images I and J of size $m \times n$, it is defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \|I(i,j) - J(i,j)\|^2$$

And the PSNR is obtained by a logarithmic ratio of base 10 given by:

$$PSNR = 10 \log \left(\frac{MAX_I^2}{MSE} \right) = 20 \log \left(\frac{MAX_I}{\sqrt{MSE}} \right)$$

where $MAX = 2^B - 1$ and B is the number of bits used in the image. Higher values of PSNR indicate better restorations.

- SSIM is a perceptual image similarity metric that was proposed as an alternative to MSE and PSNR to increase correlation with subjective evaluation. For the original and reconstructed images I and J , the SSIM is defined as:

$$SSIM(I, J) = \frac{(2\mu_I\mu_J + C_1)(2\sigma_{IJ} + C_2)}{(\mu_I^2 + \mu_J^2 + C_1)(\sigma_I^2 + \sigma_J^2 + C_2)}$$

where μ , σ and σ_{IJ} are the mean, variance and covariance of the images, respectively.

Proposed method

The proposed method is based on the assumption that the more similar the input is to its expected

output, the better a cGAN neural network performs. It is then expected that, by applying the dark channel before training the neural network, the performance of the neural network will be increased. To conduct a performance analysis of the proposed approach, three experiments were put forward:

1) Dark channel-based technique:

The dark channel has given excellent results in dehazing tasks. However, the problem addressed is different, since the atmosphere is not homogeneous, so there is no longer a relationship between the dark channel and the distance of the objects. Nonetheless, the distance $d(x)$ from the camera to the human body is insignificant, so the dark channel has a direct correspondence with the scattering coefficient β . For this reason, the dark channel is also valid for this condition. The relationship between the dark channel and the transmission can be expressed as:

$$t(x, y) = 1 - \omega I^{\text{dark}}(x, y)$$

Substituting (1) in (5) and also considering that the atmosphere is not homogeneous, different scattering coefficients are obtained for each element (x, y) :

$$e^{-\beta(x, y)d(x, y)} = 1 - \omega I^{\text{dark}}(x, y)$$

Therefore:

$$I^{\text{dark}}(x, y) = \frac{1 - e^{-\beta(x, y)d(x, y)}}{\omega}$$

Assuming constant body distance and $\omega = 1$:

$$I^{\text{dark}}(x, y) = 1 - e^{-d\beta(x, y)}$$

We can say that the relation of the dark channel to the transmission is now a function of the coefficient and the particle density β in each pixel, proving useful for effect removal.

The implemented DCP-based method is shown in Figure 2.

2) Using the proposed cGAN:

Figure 3 shows a diagram of the neural network used. In Tables 1 and 2, the architecture and hyperparameters of the generator and discriminator used are shown. Adaptive moment estimation (ADAM) was used as the optimization function in the neural network. This algorithm is an extension of the stochastic gradient descent to iteratively update network weights based on training data; it has recently seen wider adoption for deep learning applications in computer vision and

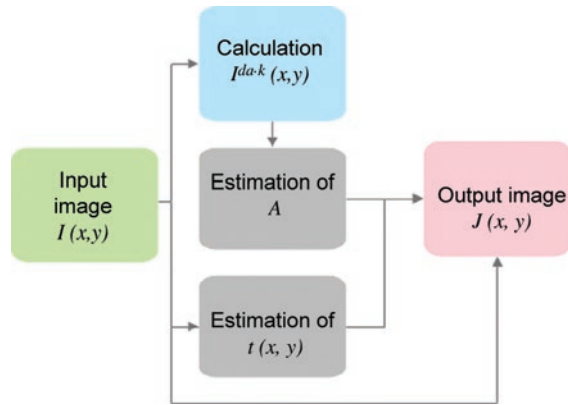


Figure 2. Method based on DCP.

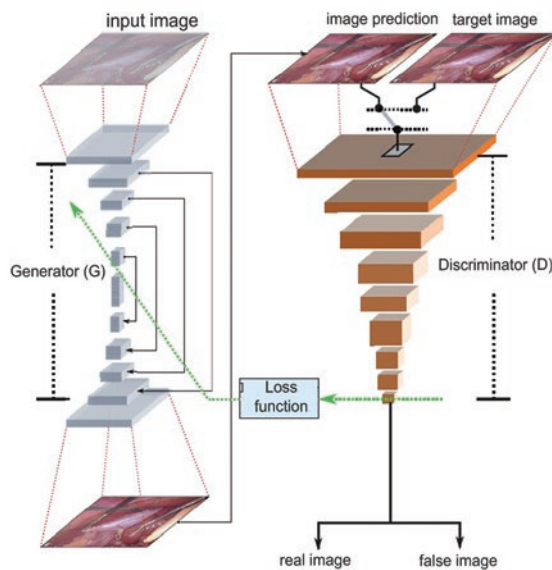


Figure 3. Method based on DCP. Diagram of the cGAN architecture. First, the input image passes through several convolutional layers until a dimensionality reduction is achieved in the middle layer of the generating structure (G). Next, an inverse process is performed with transposed convolutional layers, until an image with equal dimensionality to the input image is obtained, which will be the prediction of the image without noise (CO_2 smoke). Conversely, a discriminator (D) based on convolutional operations compares the image prediction with the target image.

natural language processing. As a loss metric, MSE is used, which is used as the loss function for regression.

3) Using a combination of the above approaches:

The input images in Figure 3 are the output images J in Figure 2. The performance evaluation for each case is depicted in Figure 4, in which the proposed methodology for evaluating the performance of the three configurations mentioned above is shown.

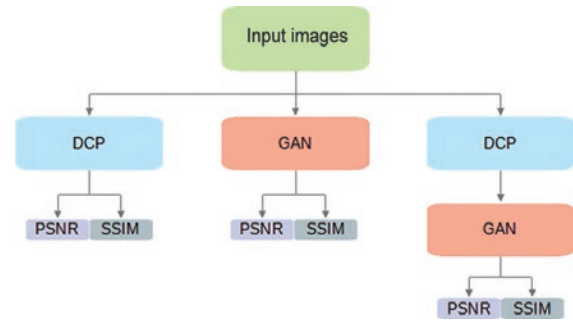


Figure 4. Proposed methodology for performance evaluation.

Configuration of the experiments

The experiments were performed on a computer with a Ryzen Threadripper 1900 processor, 128 Gb RAM and an Nvidia RTX 2080 Ti graphics card, using Linux Ubuntu 18.10, Python 3.5, OpenCV 3.3 and Keras 2.1.0 Libraries.

Results

The comparison of SSIM and PSNR metrics for the DCP, cGAN and DCP-cGAN methods is shown in Figures 5 and 6. The first important observation in these Figures is the significant improvement of the cGAN and DCP-cGAN methods over the DCP-only reconstruction, which achieved values of SSIM = 0.75 and PSNR = 20.71, while cGAN achieved values of SSIM = 0.88 and PSNR = 24.79. As for the performance between cGAN and DCP-cGAN, it is observed that the PSNR metric was slightly higher for DCP-cGAN, with a value PSNR = 25.00, versus PSNR = 24.79 achieved by cGAN. In the case of the SSIM metric, cGAN obtained a mean value of SSIM = 0.88, versus SSIM = 0.87 with DCP-cGAN. Adding a DCP pre-stage before cGAN opens a path to a deep learning architecture that focuses learning on regions of higher smoke incidence. The current results can be improved by adjusting the dark channel parameters, as well as hyperparameters such as the number of hidden layers, the number of convolutions per layer and size of filters in the convolution, among others.

Discussion

Figure 7 shows a comparison that allows us to qualitatively observe the performance of the different methods implemented. On the one hand, although the technique based only on DCP manages to significantly

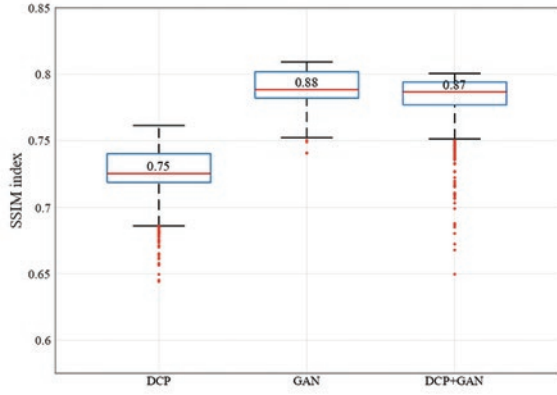


Figure 5. Comparison of the performance of the proposed methods according to the SSIM.

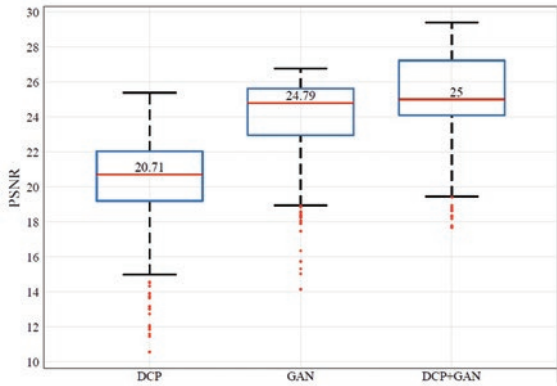


Figure 6. Comparison of the performance of the proposed methods according to PSNR.

reduce the presence of smoke in the images, an alteration in the original colors can also be seen. On the other hand, the technique based only on GAN preserves better the original colors of the image and achieves a good smoke reduction, but some fine details, mainly edges and light reflections, are altered with respect to the *ground-truth*. Finally, the proposed DCP + GAN method achieves smoke reduction while also preserving the original colors, as well as better recovery of areas with high brightness levels and edges, compared to each of the techniques alone.

Quantitative and qualitative results indicate that the combination of cGAN with a previous stage in which the dark channel is calculated helps in the identification of regions with the presence of smoke, making the generation of synthetic images by cGAN focus more on such regions than on the rest of the image. Something very important to mention is that, although a better performance is visualized with the proposed DCP + cGAN method, the advantage is not significant in

Table 1. Architecture of the generating network used

Layer	Conv	Kernel	Branch	Definition	Size
1	64	4	2	Conv - > Batchnorm- > Leaky ReLU	(256, 256, 4)
2	128	4	2	Conv - > Batchnorm- > Leaky ReLU	(128, 128, 128)
3	256	4	2	Conv - > Batchnorm- > Leaky ReLU	(64, 64, 256)
4	512	4	2	Conv - > Batchnorm- > Leaky ReLU	(32, 32, 512)
5	512	4	2	Conv - > Batchnorm- > Leaky ReLU	(16, 16, 512)
6	512	4	2	Conv - > Batchnorm- > Leaky ReLU	(8, 8, 512)
7	512	4	2	Conv - > Batchnorm- > Leaky ReLU	(4, 4, 512)
8	512	4	2	Conv - > Batchnorm- > Leaky ReLU	(1, 1, 512)
9	512	4	2	Deconv - > Batchnorm- > ReLU - >Dp(0.5)	(2, 2, 1024)
10	512	4	2	Deconv - > Batchnorm- > ReLU - >Dp(0.5)	(4, 4, 1024)
11	512	4	2	Deconv - > Batchnorm- > ReLU - >Dp(0.5)	(8, 8, 1024)
12	512	4	2	Deconv - > Batchnorm- > ReLU - >Dp(0.5)	(16, 16, 1024)
13	512	4	2	Deconv - > Batchnorm- > ReLU	(32, 32, 1024)
14	256	4	2	Deconv - > Batchnorm- > ReLU	(64, 64, 512)
15	128	4	2	Deconv - > Batchnorm- > ReLU	(128, 128, 256)
16	64	4	2	Deconv - > Batchnorm- > ReLU	(256, 256, 128)
17	3	4	2	Tanh	(512, 512, 3)

statistical terms, since as can be seen in Figures 5 and 6, there is an overlap in the boxplots. Nevertheless, the results are a good starting point for the experimentation of a more refined mixture of concepts.

Conclusions

This article proposes a method to improve the reduced visibility in laparoscopic images caused by visual obstruction due to the smoke generated by tissue combustion during surgery. The proposed method is



Figure 7. Comparison of the results as per the methods used. **A:** input images with synthetic CO_2 smoke. **B:** DCP. **C:** GAN. **D:** DCP + GAN. **E:** ground-truth.

based on the combination of a classical processing method, the DCP, and an artificial intelligence method, the cGAN. This method is able to reduce the influence of smoke on the output image and recover the color gamut similar to that of the original image, showing that

a hybrid method can increase the performance of other methods. This combination of techniques has been shown to have a high performance in the reconstruction of target images, according to the PSNR and SSIM metrics used in the present work.

Table 2. Architecture of the discriminative neural network used

Layer	Conv	Kernel	Branch	Definition	Size
1	64	4	2	Conv -> Batchnorm- > Leaky ReLU	(256, 256, 4)
2	128	4	2	Conv -> Batchnorm- > Leaky ReLU	(128, 128, 128)
3	256	4	2	Conv -> Batchnorm- > Leaky ReLU	(64, 64, 256)
4	0	0	0	ZeroPadding2D	(32, 32, 512)
5	512	4	1	Conv	(16, 16, 512)
6	0	0	0	BatchNorm - > Leaky ReLU - > ZeroPadding	(8, 8, 512)
7	1	4	1	Conv	(4, 4, 512)

This article opens a new panorama in related research by showing that the mixture of a classical method with an artificial intelligence one can outperform the results of both in isolation. As future work, it is expected to improve the behavior of the cGAN by adding a loss function specially designed for the resolution of the exposed problem. Alternatively, an exhaustive search of the parameters in the dispersion model is planned in order to adjust the preprocessing stage at the input of the cGAN.

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Conflicts of interest

The authors declare they have no conflicts of interest.

Ethical disclosures

Protection of people and animals. The authors declare that no experiments have been made on human beings or animals for this research.

Data confidentiality. The authors declare that they have followed their work center's protocols for the publication of patient's data.

Right to privacy and informed consent. The authors have received an informed consent from the patients and/or subjects referred to in this article. This document is in possession of the corresponding author.

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