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Features for detecting smoke in laparoscopic videos

Abstract: Video-based smoke detection in laparoscopic surgery has different potential applications, such as the automatic addressing of surgical events associated with the electrocauterization task and the development of automatic smoke removal. In the literature, video-based smoke detection has been studied widely for fire surveillance systems. Nevertheless, the proposed methods are insufficient for smoke detection in laparoscopic videos because they often depend on assumptions which rarely hold in laparoscopic surgery such as static camera. In this paper, ten visual features based on motion, texture and colour of smoke are proposed and evaluated for smoke detection in laparoscopic videos. These features are RGB channels, energy-based feature, texture features based on gray level co-occurrence matrix (GLCM), HSV colour space feature, features based on the detection of moving regions using optical flow and the smoke colour in HSV colour space. These features were tested on four laparoscopic cholecystectomy videos. Experimental observations show that each feature can provide valuable information in performing the smoke detection task. However, each feature has weaknesses to detect the presence of smoke in some cases. By combining all proposed features smoke with high and even low density can be identified robustly and the classification accuracy increases significantly.

Keywords: Laparoscopic videos, smoke detection, HSV colour space

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1 Introduction

Smoke in laparoscopic surgery is typically appears due to the use of electrocautery when cutting or coagulating tissues. Detecting smoke in laparoscopic images has various conceivable applications, such as retrieving surgical events associated with electro-surgery tasks and developing automatic smoke evacuator.

Many researches have been conducted during the last years to detect smoke based on videos for fire surveillance applications. Generally, video-based smoke detection methods are based on extracting features of suspected smoke areas and embedding these features into a relevant classification system. In [3] depending on histogram of oriented objects (HOGs) and histogram of optical flow, candidate blocks of smoke were localized and a bag of word model was used with energy and colour features to get the best results using SVM. In [9], image energy and colour information were used as essential features to detect smoke. In a recent publication [5], an optical flow and texture based algorithm was proposed. Static texture features were extracted using local binary pattern (LBP) and local binary pattern variance (LBPV) and optical flow was used to extract the motion feature.

All the previous methods shared common assumptions that rarely hold in laparoscopic videos. For instance, the camera is static allowing background subtraction as the initial step to determine suspected smoke areas. Another difference is that camera in fire surveillance systems is located far away and the smoke is slowly covering the field of view (FOV). In comparison, in laparoscopic videos the camera is located close to the tissue and the smoke diffuses rapidly. Loukas [6] proposed an algorithm to detect smoke in laparoscopic videos that overcomes the above-mentioned limitations. Various *ad hoc* kinematic features were extracted from the optical flow of a grid of particles to classify video shots into smoke or non-smoke frames.

In this paper, we address the problem of detecting smoke in laparoscopic surgery depending on colour characteristics, motion and texture patterns of smoke. Ten features were experimentally identified from cholecystectomy videos. An evaluation of each feature individually was performed using logistic regression.

2 Method

The purpose of this paper is to identify different visual features extracted from the laparoscopic videos and evaluate the ability of each feature in generating good smoke detection results. According to empirical observations, we define three types of smoke in laparoscopic images, these are emitted smoke, smoke particles and fog (see **Figure 1**).

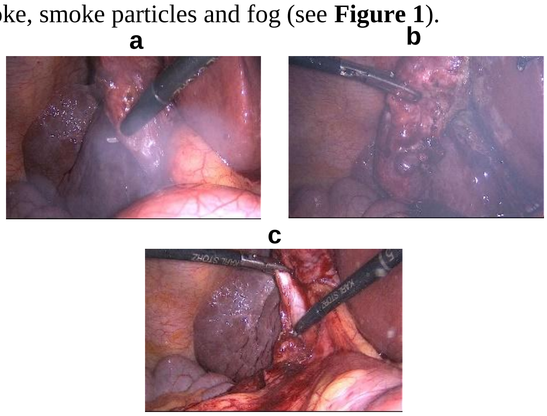

Figure 1: smoke types in cholecystectomy videos: (a) emitted smoke, (b) Fog, (c) smoke particles.

Various features related to colour, motion and texture patterns were experimentally tested on different shots extracted from four cholecystectomy videos. Ten features were extracted and individually evaluated on the entire videos. The videos are full HD (1920*1080) and acquired at 25fps. Logistic regression was used for evaluation.

2.1 Normalized-RGB features

The presence of smoke affects the R, G, and B channels by decreasing or increasing the colour channel value depending on its brightness. The normalized-RGB features, which are calculated by dividing each of the R, G and B channels by their sum as shown in equation (1), are light invariant and they describe the chromatic information regardless of illuminance conditions [4]. Furthermore, the change of these features is more obvious than RGB channels when the smoke appears in the scene because each feature represents the frame content percentage of respective colour which shows not only the colour channel information but also the correlation with the other colour channels.

$$\mathbf{r} = \frac{\mathbf{R}}{\mathbf{R+G+B}}\ , = \frac{\mathbf{G}}{\mathbf{R+G+B}}, \mathbf{b} = \frac{\mathbf{B}}{\mathbf{R+G+B}} \qquad \mathbf{(1)}$$

Smoke has great influence on **r** and **b** features. **r** decreases as the smoke covers the anatomical structure, while **b** increases since the smoke has whitish-blue colour. Consequently, when smoke appears **b**, which is much lower than **r**, rises reaching proximity to **r** or even exceed it depending on the smoke density.

2.2 Wavelet energy

2D-wavelet decomposition of type "Haar" at level 1 was applied on each frame to obtain four sub-images HL, LH, HH and LL. HL, LH, HH contain high frequency coefficients in vertical, horizontal and diagonal direction respectively, whereas LL contains low frequency coefficients of decomposed frame. The energy was calculated and normalized as shown in equation (2). The high frequency content of the image is reduced as the smoke appears in the scene and the edges get blurred. Thus, reduction in the energy is a clue to the presence of smoke.

$$\mathbf{E} = \frac{\sum(|\mathbf{HL}|+|\mathbf{LH}|+|\mathbf{HH}|)}{\sum(|\mathbf{LL}|)} \qquad (2)$$

2.3 GLCM texture features

Gray level co-occurrence matrix (GLCM) represents the probability of pixel gray level occurrence in a specific orientation and within a certain distance with respect to another pixel gray level. Since the GLCM requires high computational time, GLCM were calculated only in the angle of 90° and distance of one pixel to obtain the following three features:

$$\mathbf{Entropy} = \sum_{i=1}^{N}\sum_{j=1}^{N} \boldsymbol{C(i,j).log_2 C(i,j)}\ ,$$

$$\mathbf{Correlation} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} i.j.C(i,j)-\mu_x.\mu_y}{\sigma_x\sigma_y}\ ,$$

$$\boldsymbol{Contrast} = \sum_{i=1}^{N}\sum_{j=1}^{N}(\boldsymbol{i-j})^2.\boldsymbol{C(i,j)}\ ,$$

where N is the number of gray levels; C(i,j) is an element of GLCM; m_x resulted by summing each GLCM's column $m_x = \sum_{j=1}^{N} C(i,j)$ and m_y resulted by summing each GLCM's raw $m_y = \sum_{i=1}^{N} C(i,j)$; μ_x, μ_y, σ_x and σ_y are the mean and standard deviation of $m_x$and m_y [7,8].

2.4 HSV colour space feature

Smoke presence in the images affects the saturation and value channels in the HSV colour space. When the smoke covers the FOV the saturation of the colours decreases, and the histogram of the S channel will be shifted to the left side. Empirically we noticed that the histogram of S channel, particularly between 0.4 and 0.6, is influenced by smoke and the number of pixels whose saturation level between those two thresholds could be an excellent feature to detect the presence of smoke in laparoscopic videos.

2.5 Fog area and optical flow features

When surgeons use electrocautery to dissect tissues the endoscopic camera is almost static. The movement in the scene could result from the instrument, tissues, or the smoke. One of the possible scenarios, the moving regions are specified. Then, using adequate thresholds of the colour channels the candidate smoke regions are detected. Indeed, this could be the best scenario except for the case of fog. Hence, another area was also estimated by applying the same thresholding on the entire frame.

- Detecting moving region:

The Horn-Schunck optical flow algorithm [6] was used to detect the moving pixels between the current frame and the previous one. Since the camera is not static, almost all pixels are moving, but the pixels related to smoke, instruments and manipulated tissues have the largest movement. Consequently, the pixels moving more than a specific threshold was considered as moving regions.

- Extracting region corresponding to smoke colour in HSV colour space:

The frame in RGB colour space is converted into HSV colour space. Then, by setting low and high thresholds of h, s, channels, the regions related to smoke are detected. We applied some morphological process to get rid of connected components that are not related to smoke. The areas of the segmented regions are provided to the classifier.

3 Result

The proposed features were tested on four manually annotated cholecystectomy videos to detect smoke. **Figure 2** shows the features extracted from one video with corresponding videogram and smoke annotation. In addition to experimental observation, Logistic regression was employed to evaluate the efficiency of each feature to identify smoke and non-smoke frames. The dataset was partitioned into two subgroups for training and testing i.e. 50% for training the logistic regression model and 50% for evaluation. The results show that some features are biased to detect smoke frames rather than non-smoke frames, while the other do the opposite. To assess the efficiency of each feature, the true positive (TP) i.e. correctly detected smoke frames, and the true negative (TN) i.e. correctly detected non-smoke frames were calculated and organized in **Table 1**:

Table 1: Classification performance of each feature using logistic regression

Feature	TP	TN	Total Accuracy
Red	73.7%	68%	70.2%
Green	73%	63%	66.8%
Blue	67.6%	54.7%	59.8%
Fog Area	50%	72.66%	63.6%
Optical Flow	59%	69.3%	63.1%
HSV	78.1%	73.1%	75%
Energy	69%	51%	59%
Entropy	75.1%	42.7%	55.6%
Contrast	69.9%	58.6%	63.1%
Correlation	84.9%	43.6%	59.9%

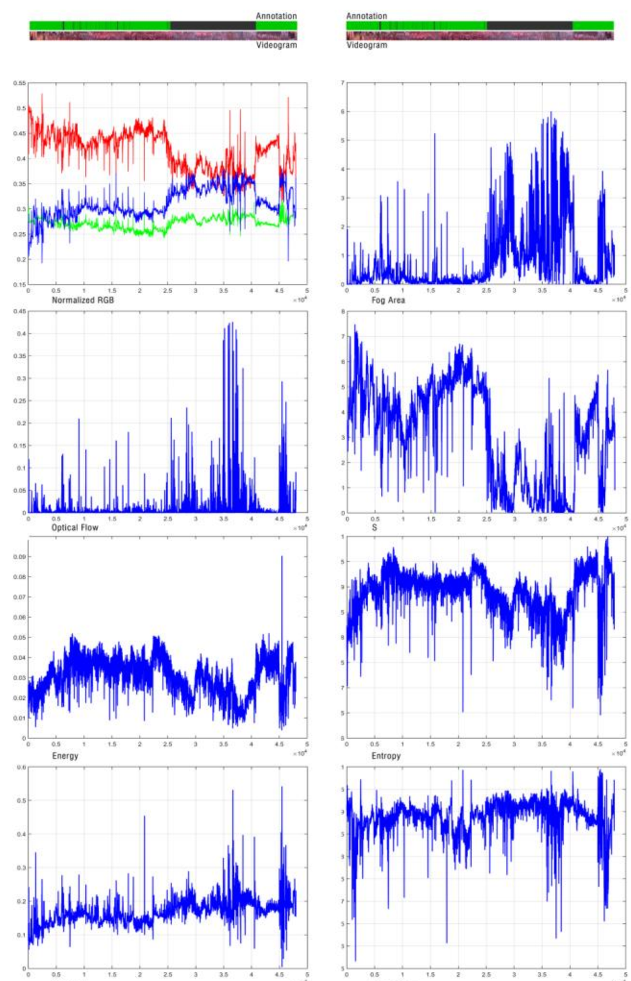

Figure 2: Extracted 10 features for entire cholecystectomy video with videogram and smoke annotation (green refers to non-smoke frames, black refers to smoke frames).

4 Discussion

In this paper, we proposed and evaluated ten visual features based on chromatic, dynamic and texture characteristics to detect smoke presence in laparoscopic videos. We focused on the visual features that are affected by the appearance and dynamic characteristics of smoke. Three patterns of smoke were observed: (i) emitted smoke, (ii) fog and (iii) smoke particles (see **Figure 1**). Typically, emitted smoke is associated with the use of electrocautery to cut or coagulate tissues. Moreover, emitted smoke is generated at the point where the electrocautery is applied and fast diffuses and covers large area of the scene. Fog appears due to accumulating of smoke generated by electrocautery in the abdominal cavity. Empirical observations show that fog appears in cholecystectomy after clipping and division of cystic duct and artery, where no smoke evacuation is established. On the other hand, smoke particles appear in laparoscopic images after many usages of electrocautery, these particles almost appear in the whole laparoscopic video and they are difficult to detect. Since smoke particles do not significantly affect the FOV and are not related to any surgical task, it is not important to detect smoke particles in laparoscopic videos. Therefore, only the emitted smoke and the fog were considered in our contribution.

Experimental results show that the proposed features are promising, despite of their shortcomings. To figure out the shortcomings of each feature, we carried out a retrospective analysis of the examined videos and particularly the misclassified frames. In general, the misclassification based on any of the previous features is resulting from the unpredictable rapid change of the scene. For instance, the normalized red and blue features are oppositely influenced by smoke which has a whitish-blue colour leading to lowering the former feature and rising the latter. However, when a reddish organ or tissue holds close to the camera with presence of smoke, the normalized red feature increases instead of decrease. In this context, another example is related to smoke area and optical flow features where specific thresholds were used to extract the smoke area features. These thresholds were chosen depending on the observations of two cholecystectomy videos. Therefore, further improvement could be by optimizing these thresholds on larger dataset. Applying each feature individually yields moderate classifying performance which could be improved by combining the features to counter the aforementioned shortcomings.

In the future, we plan to combine these features and provide them into adequate classifier to test their ability to detect smoke in laparoscopic videos.

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Author's Statement

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