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Classifying smoke in laparoscopic videos using SVM

Abstract: Smoke in laparoscopic videos usually appears due to the use of electrocautery when cutting or coagulating tissues. Therefore, detecting smoke can be used for event-based annotation in laparoscopic surgeries by retrieving the events associated with the electrocauterization. Furthermore, smoke detection can also be used for automatic smoke removal. However, detecting smoke in laparoscopic video is a challenge because of the changeability of smoke patterns, the moving camera and the different lighting conditions. In this paper, we present a video-based smoke detection algorithm to detect smoke of different densities such as fog, low and high density in laparoscopic videos. The proposed method depends on extracting various visual features from the laparoscopic images and providing them to support vector machine (SVM) classifier. Features are based on motion, colour and texture patterns of the smoke. We validated our algorithm using experimental evaluation on four laparoscopic cholecystectomy videos. These four videos were manually annotated by defining every frame as smoke or non-smoke frame. The algorithm was applied to the videos by using different feature combinations for classification. Experimental results show that the combination of all proposed features gives the best classification performance. The overall accuracy (i.e. correctly classified frames) is around 84%, with the sensitivity (i.e. correctly detected smoke frames) and the specificity (i.e. correctly detected non-smoke frames) are 89% and 80%, respectively.

Keywords: smoke detection, laparoscopy, HSV colour space, texture features, optical flow, SVM classifier.

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1 Introduction

Laparoscopic videos are a very important source of surgical data that could provide relevant information without affecting the flow of surgical procedure. In particular, smoke is generated during laparoscopy due to the use of electrocautery. Therefore, smoke detection in laparoscopic videos could be used to address the occurrence of a surgical event associated with the electrocauterization.

In addition to event-based annotation and retrieving, smoke detection depending on the visual features extracted from the laparoscopic videos is considered an important step towards the developing of automatic smoke removal. Automatic smoke removal has certain benefits e.g. [1] showed that automatic smoke evacuation makes the field of view better and reduces the risks of chemical compounds of smoke on the patient and the surgical team.

Smoke detection based on videos have been studied widely in the past years for fire surveillance systems. In general, the video-based smoke detection algorithm includes extracting the potential area of smoke by detecting the moving objects, then the features of these areas are extracted and provided into an adequate classifier. In [2], candidate blocks are localized after background subtraction, and Histogram of oriented objects (HOGs) and Histogram of optical flow are constructed of the blocks. A bag of word model is employed with energy and colour features to get the best results using SVM. Another approach was exploited in [3] by analyzing normalized-RGB features and spatial energy-based features of the candidate smoke region in the temporal domain before combining them using SVM classifier. In a recent publication [4], 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 above-mentioned approaches often depend on assumptions which rarely hold in laparoscopic surgery. One of these assumptions is that the camera is static. Thus, allowing background subtraction to determine the suspected area of smoke. Another assumption, the smoke is moving in the upward direction and slowly covers the observed area

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since the surveillance camera is located far away [5]. None of the previous methods is adequate for smoke detection generated by tissue cauterization in laparoscopy. Loukas [5] proposed an algorithm, which overcomes the previous limitations, to classify video shots of cholecystectomies into smoke or non-smoke shots. This algorithm depends on using optical flow to track a grid of particles placed on the initial frame in time-space, then some kinematic features are extracted, at the end the classification was done using one class support vector machine (OCSVM).

In the present study, we propose an approach for smoke detection that overcomes the aforementioned limitations and provides the ability to detect smoke in laparoscopic videos based on multiple features. These features are: red, green and blue channels, energy-based feature, texture features based on gray level co-occurrence matrix (GLCM), features based on the detection of moving regions using optical flow and HSV colour space. Different combinations of these features were evaluated on laparoscopic videos using SVM classifier.

2 Method

2.1 Data

Four laparoscopic videos (258333 frames) were used to validate our algorithm. The videos are full HD (1920*1080) and acquired at 25fps. These videos were manually annotated as smoke or non-smoke images.

2.2 Feature extraction

The proposed smoke detection algorithm is based on extracting ten features from each laparoscopic frame. The extracted features are used as input for the SVM classifier. The ten features reflect the following [6]:

- The presence of smoke leads to blurring edges which reduces the high frequencies component in the image.
- The rgb components and sv components in RGB and HSV colour spaces change because smoke colour is whitish-blue.
- Mainly two kinds of smoke can be recognized in laparoscopic videos; those are the emitted smoke and the fog [6]. Emitted smoke typically appears when the surgeon is using electrocautery. Smoke starts from the cutting point, expands in adjacent frames and then disappears. On the other hand, fog appears after continuous use of electrocautery and no smoke removal is established.
- Brightness transition over frames due to smoke.

2.2.1 Normalized-RGB features

The normalized-RGB features, calculated as shown in equation (1) are light invariant and they describe the chromatic information regardless of the illuminance condition [3]. Each feature reflects not only the chromatic information of respective colour channel but also the correlation with the other colour channels.

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

2.2.2 Wavelet energy

Due to the semi-transparent nature of smoke, it obscures edges which may disappear when the smoke density is high. Consequently, image sharpness which relates to high-frequency content is reduced [3]. We decomposed each frame by 2D-wavelet transformation of type “Haar” at level 1 and the energy was calculated as shown in equation (2).

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

HL, LH, HH and LL are wavelet sub-images. HL, LH and HH contain high frequency coefficients in vertical, horizontal and diagonal direction respectively, whereas LL contains low frequency coefficients of the decomposed frame.

2.2.3 GLCM texture features

Due to smoke edges get blurred and thereby the image get smoothed. Smoothness and structure are estimated by texture features. Three texture features were calculated using equations (3). The gray level co-occurrence matrix (GLCM) of a respective frame was calculated at angle 90º.

$$\begin{aligned}
&\mathbf{Entropy} = \sum_{i=1}^{N}\sum_{j=1}^{N} \boldsymbol{C(i,j).\,log_2 C(i,j)},\\
&\mathbf{Correlation} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} i.j.C(i,j)-\mu_x.\mu_y}{\sigma_x\sigma_y},\\
&\boldsymbol{Contrast} = \sum_{i=1}^{N}\sum_{j=1}^{N}(\boldsymbol{i-j})^2.\,\boldsymbol{C(i,j)}\ ,
\end{aligned} \qquad (3)$$

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 [6].

2.2.4 HSV colour space feature

Experimentally we noticed that the histogram of saturation channel (S) in HSV colour space is affected by the smoke

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presence especially in the range between 0.4 – 0.6. Therefore, the number of pixels whose saturation lies in this range was used as a feature for detecting smoke [6].

2.2.5 Optical flow feature

Smoke emits and moves over the scene as the surgeon uses the electrocautery device. To detect moving objects, the Horn-Schunck optical flow algorithm was used. A specific threshold was applied to ignore the small pixels' movement. Since the camera is not static, the detected objects could be tissues, instruments or smoke. Therefore, to detect the objects related to smoke, thresholding in HSV colour space were carried out followed by some morphological processing to get rid of connected components that are not belonging to smoke [6].

2.2.6 Fog Area

Smoke accumulates in the abdominal cavity after performing many successive electrocauterization procedures and no smoke evacuation is involved. Consequently, all the scene is covered by smoke which appears as fog and has no dynamical features like emitted smoke. Similar to optical flow feature thresholding in HSV colour space was implemented on the image to get the area related to fog.

2.3 Classification using SVM

In our implementation SVM classifier with radial basis function (RBF) kernel was utilized. To estimate the optimal parameter value for RBF kernel, a 10-fold cross-validation was executed on the training set.

The dataset was randomly divided into two equal subgroups. One subgroup was used for training the SVM classifier, while the other was used to test the classifier response. Evaluation of all features besides different feature subsets was done.

3 Result

The above-mentioned features were defined for the entire videos. **Figure 1** shows the proposed features extracted from a sequence of 100 frames in which smoke appears from frame 50th to 70th. **Figure 1** illustrates that some features decrease as smoke appears in the scene while others increase.

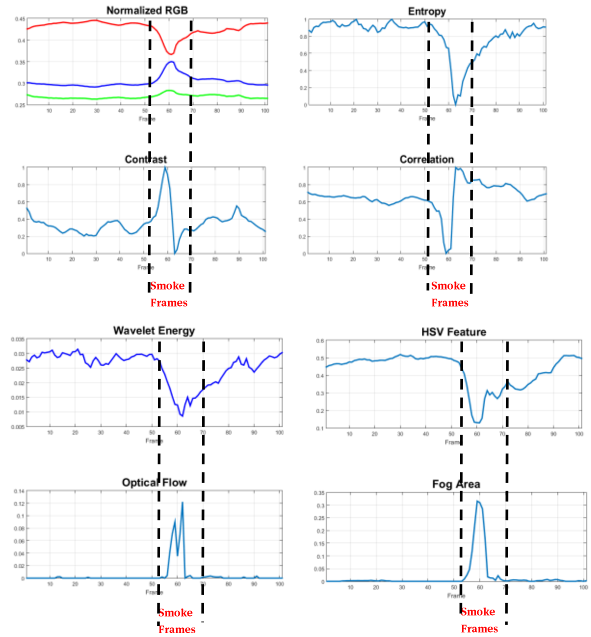

Figure 1: Extracted 10 features from 100 frames with smoke annotation.

Table 1 and **Figure 2** show the classification results. The true positive (TP) i.e. correctly detected smoke frames, the true negative (TN) i.e. correctly detected non-smoke frames, the false positive (FP) i.e. non-smoke frames recognised as smoke frames, and the false negative (FN) i.e. smoke frames recognised as non-smoke frames were calculated and shown in Table 1. The penalty parameter C and kernel parameter γ of the RBF SVM classifier were optimized using 10-fold cross-validation approach over the training set for the different feature subsets. The optimum values, when applying the whole features, were identified as $C=8.74$ and $\gamma=3.55$.

Table 1: classification performance using different feature subsets

	RGB (V1)	Texture & Energy (V2)	Saturation V(3)	Emitted smoke & Fog Areas (V4)	V(1) & V(3) & V(4)	All features
TP	79.8%	80%	80.9%	60.5%	88%	92%
TN	71%	78.2%	64.7%	73.7%	87%	91%
FN	20.2%	20%	19.1%	39.5%	12%	8%
FP	29%	21.7%	35.3%	26.3%	13%	9%
Overall Accuracy	74.7%	79%	71.5%	68.3%	87.4%	91.4%

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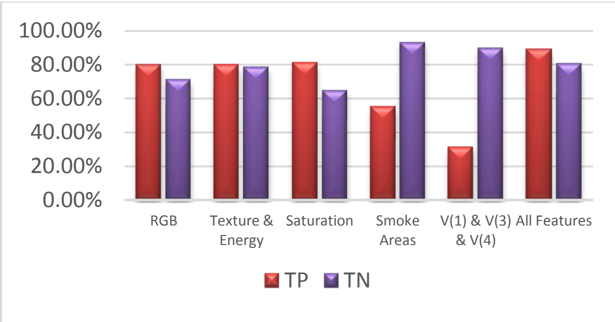

Figure 2: True positive and True negative classification results of different feature subsets

4 Discussion

In this paper, we introduced a method for detecting smoke in laparoscopic videos. Smoke in laparoscopic images is generated due to the use of electrocautery to cut or coagulate tissues. Smoke diffuses rapidly inside the abdominal cavity and covers large area of the FOV. We proposed a method for smoke detection. This method depends on combining multiple features related to colour, motion and texture patterns of smoke. To evaluate the performance of our algorithm, four manually annotated cholecystectomy videos were used.

Loukas [5] proposed an algorithm depends on combining multiple kinematic features extracted from video shots of the procedure. Three cholecystectomy videos were decomposed into successive frames and each of which was classified into smoke or non-smoke frame. In fact, it is the difficult to predefine all types of non-smoke movement during the laparoscopy. And that could interpret the low accuracy acquired on the third video where the operation was performed by surgical team with moderate experience. Therefore, additional features should be added to improve the performance of this algorithm. In [5], a comparison with discrete wavelet transform for detecting smoke in laparoscopic videos was performed. The DWT showed moderate performance and the maximum accuracy was 63%. We emphasize that employing one of the previous features for detecting smoke in laparoscopic videos is not sufficient. On the other hand, combining all previous features yielded sufficient recognition accuracy.

The experimental results show that our algorithm can detect the presence of smoke with various forms such as fog, low and high density. In the manual annotation, we considered the frames with very low smoke density as smoke frames. Reviewing our results showed that many of the misclassified frames are related to frames with very low smoke density. Therefore, by considering these frames as non-smoke frames the total accuracy could be enhanced. A limitation of the study was the low number of annotated videos so only four videos were included.

Since the frame probability of containing smoke is related to the state of previous frames, further work should consider the temporal aspect to decrease the misclassified frames within smoke frame series. For future work, we plan to investigate the detection of other surgical events depending on visual features.

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Author's Statement

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