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Indoor Video-Based Smoke Detection using Gaussian Mixture Model and Motion-based Tracking

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Abstract

Smoke is the leading cause of death due to suffocation as fire emits smoke earlier than other signatures throughout fire growth and development stages. Thus, its rapid detection can maximize the probability of successful fire suppression and survivability. Traditional methods detect smoke but are inefficient when under certain circumstances. However, video-based smoke detection is increasingly popular, although most did not study its dynamic characteristics such as its motion, speed, and environmental factors. This study presented a method for indoor video-based smoke detection composed of a static detection of foreground or moving pixels using GMM and the dynamic detection through motion object tracking using Kalman Filter to verify and analyze the smoke behavior. The results showed that the algorithm detected smoke effectively given varied test circumstances. Although, it also detects non-smoke objects since the algorithm focuses on detecting moving objects. This study contributes an algorithm for developers working on alarm systems and similar works.

Keywords: smoke detection algorithm, motion-based tracking, GMM, Kalman filter, foreground detection

Introduction

Fire usually starts from smoke, and its dynamic characteristics trigger a fire. Hence, early smoke detection is vital to save lives, properties, and even possible untoward and uncontrollable proliferation of blazes. In addition, due to the natural impact of the wind, the smoke has various dynamic features such as direction, diffusion, and disorder (Wang et al., 2016; Wang et al., 2017). Besides, the smoke's composition will produce different colors (Wang et al., 2016; Cazzolato et al., 2017; Peng & Wang, 2019).

Most reported fire cases in the U.S. occurred at homes, causing deaths, injuries, and loss of properties (Ahrens, 2017), with an estimated average of 15,970 fires caused by dryers or washing machines (Campbell, 2017) occurring indoors or in semi-closed spaces. Moreover, a higher incidence of deaths is from home fires that do not have a working smoke alarm system (Istre et al., 2014) or fire sprinklers resulting in higher treatment costs for affected patients (Banfield et al., 2015). In the Philippines, statistics showed from January to December 2013 that 12,301 fire accidents were due to overloading, and electrical glitches, which often occur indoors, are the leading causes of fire incidents (Canoy, 2014).

However, smoke inhalation injuries usually cause fire deaths (Gupta et al., 2018), especially indoor fires. Various particles compose a smoke where chemicals attribute to its visibility, which often causes more damage to a building than flames. A wide range of methods detects blazes using smoke (Kwak et al., 2016; Appana et al., 2017; Umar et al., 2017) to prevent further damage to properties and casualties due to fire. Typical technologies widely used today are conventional and addressable smoke detection using sensors. Besides, the earliest smoke detection reliability is not absolute (Favorskaya et al., 2015). The distance of the sensors to the source of the smoke is a typical reason for the limited early smoke detection. Besides, the sensors cannot detect the smoke efficiently due to deteriorating features (Tian et al., 2014) or irregular shapes and color variations (Peng & Wang, 2019). With advances in sensors,

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microelectronics, and information technologies, many new fire detection techniques and concepts continually develop through video.

Video-based smoke detection is becoming a popular approach to detecting smoke and still developing. One successful model for detecting smoke uses Gaussian Mixture Model (GMM) for foreground segmentation than the conventional Bayesian approaches (Pagar & Shaikh, 2013), separating any moving or foreground object from the background image in the video sequence. GMM method can detect objects even if the surrounding is unclear due to the illumination changes and other environmental effects. Moreover, the delay and variance of the Gaussian mixture model determined which Gaussian distribution corresponds to the background (Pagar & Shaikh, 2013).

Dynamic analysis of smoke is necessary to achieve a high-reliability rate as it verifies smoke by segmentation (Jia et al., 2016; Cazzolato et al., 2017), extracting foreground objects (Yu et al., 2013). In addition, smoke disorder or change in scale is one of its most observed features since it spreads in different directions. Hence, the smoke detection approach used the maximum value of the binary image for each frame to determine if its direction was going upwards (Narwade & Chakkarwar, 2013; Pagar & Shaikh, 2013; Wang et al., 2016). Also, another approach used smoke disorder based on the ratio of the region's perimeter and area and diffusion to verify whether the segmented region is smoke or not (Jia et al., 2016) or by tracking and analyzing moving objects to recognize their behaviors considering the different directions they are going (Barmpoutis et al., 2014). Hence, tracking the moving objects captured in a video.

Video tracking is an action that estimates the object's trajectory or path in the image plane when it moves in a video. The tracker assigns labels consistently to the tracked objects by detecting the localized regions continuously, points, or features of an image for every frame (Patel & Thakore, 2013; Gunjal et al., 2018). Object tracking predicts the object's position from the previous information. It verifies the existence of every object at the predicted position after the motion model learned some sample of image sequences before performing them (Patel & Thakore,

2013; Gunjal et al., 2018). An approach to smoke detection combines block image processing and optical flow techniques to extract areas that might be smoke (Yu et al., 2013; Zhao et al., 2015), thereby segmenting complex backgrounds within the suspected smoke regions (Jia et al., 20116). Also, detecting smoke using static and dynamic smoke features showed a potential approach (Wang et al., 2016; Wang et al., 2017). Nevertheless, there is a doubt whether the algorithms have high false alarms and detection failures. Most test videos used have smoke and only neglect some movements in exact scenarios.

Many video-based algorithms can detect if there is smoke or not in a video sequence. However, detecting smoke with various dynamic settings, such as the different moving objects on a video, still needs further study. Hence, the study proposed an approach to detecting smoke using GMM for background subtraction and motion-based tracking using the Kalman filter technique to verify smoke after behavior analysis. This approach aimed to contribute to the ongoing studies on detecting smoke efficiently and accurately in a dynamic environment wherein several factors may occur. Hence, tracking every single movement on an actual scenario, which is not only smoke is moving, and analyzing their motion to verify a smoke or not. This study is beneficial for further investigation and development of smoke detection through image processing and the basis for future enhancement and development in any interrelated fields.

Materials and Methods

Conceptual Framework

The study used two phases, the static and dynamic analysis, to detect the smoke. Static analysis involves foreground detection using Gaussian Mixture Model (GMM), an effective tool in background modeling, noise eliminations using morphological operations, and blob analysis. On the other hand, the dynamic analysis includes motion-based object tracking using Kalman Filter. Figure 1 shows the conceptual framework of the study.

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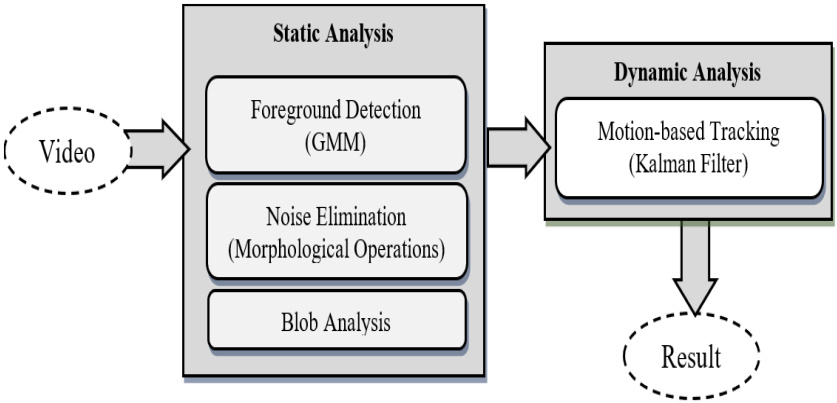

Figure 1. Video smoke detection conceptual framework.

The framework presented in Figure 1 starts with designing the static analysis, followed by the dynamic analysis. The static analysis phase preprocessed the captured video for further analysis requiring the video sequence for analysis in separating foreground and background objects. The preprocessing performed three major activities – extracted the foreground, removed the noise in the image, and performed blob analysis to calculate the regions necessary for the motion-based tracking.

The algorithm initially focuses on detecting the video's foreground, removing the static background from the workspace while highlighting the moving object in the foreground. The process starts with the Gaussian Mixture Model detecting the foreground object from the video sequence. Next, the detected foreground object underwent morphological processes to eliminate the noise. Then, the clear foreground area underwent blob analysis to identify the regions suitable for motion-based tracking. Once done, the foreground object is ready for the dynamic analysis. The dynamic analysis used the Kalman Filter algorithm to follow the movement of the foreground object. Finally, the algorithm plays along with the direction of the foreground object as it moves to obtain sufficient data to verify whether the moving object is smoke or not.

Rules on Motion-based Smoke Tracking

Table 1 presents the rules that detect the smoke after extracting the foreground from the background subtraction step. In the tracking using the Kalman Filter, if the suspected region of smoke appears to be consecutively visible based on the number of frames and higher than the threshold, it seems to be smoke.

Table 1. Smoke determination rules.

Moving Object (Y/N)	Tracked frames (visible object > threshold)	Type of smoke	Description
Yes	True	Smoke	Smoke detected
Yes	False	Non-smoke	-
No	-	-	-

Coding

The smoke detection algorithm used MATLAB R2014a, specifically its image processing toolbox, in designing and creating the algorithms for this video-based smoke detection study. The testing process involved five sets of videos satisfying different smoke characteristics, with each set having three pre-recorded videos being analyzed.

Algorithm Performance Evaluation

This procedure tests the accuracy of the algorithm based on the True Positive Rate (TPR) or correct detection, False Positive Rate (FPR) or a false alarm, and Missing Range (MR) or detection failure (Narwade & Chakkarwar, 2014). These tests involved the total frames in the video segregated with the number of frames with and without smoke. The test

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used different video testings with varying smoke characteristics and settings. First, the test process counts the detected frames with corresponding smoke on each test video. Then, the frames detected without smoke and compared to the number of actual frames having a smoke and non-smoke earlier set to get its detection percentage. Finally, the process calculated the average TPR, FPR, and MR based on each video testing. This rate determined how accurate the algorithm was in terms of detecting smoke.

The testing of the algorithm's performance used three pre-recorded videos for each category, as presented in Table 2, to test whether the algorithm achieved reliable motion-based smoke detection.

Table 2. Categories of test videos.

Category	Characteristic
Test Videos A	Normal Smoke
Test Videos B	Normal Smoke (Bright Setting)
Test Videos C	Normal Smoke (Dark Setting
Test Videos D	Thin Smoke
Test Videos E	No Smoke

Results and Discussion

Foreground Detection using Gaussian Mixture Model (GMM)

Foreground detection is a technique that removes the static background while extracting the moving object. This method used the Gaussian mixture model to detect objects even though the background is unclear due to the illumination changes and other environmental effects. Before extracting the foreground, the algorithm applied morphological operations to remove noise and fill the holes and gaps of the masked object. Morphological operation is an important preprocessing method to clean the image through noise reduction and determine its vividness.

Figure 2 shows a sample video frame with no morphological operation applied, and Figure 3 shows a similar video frame with morphological operations applied.

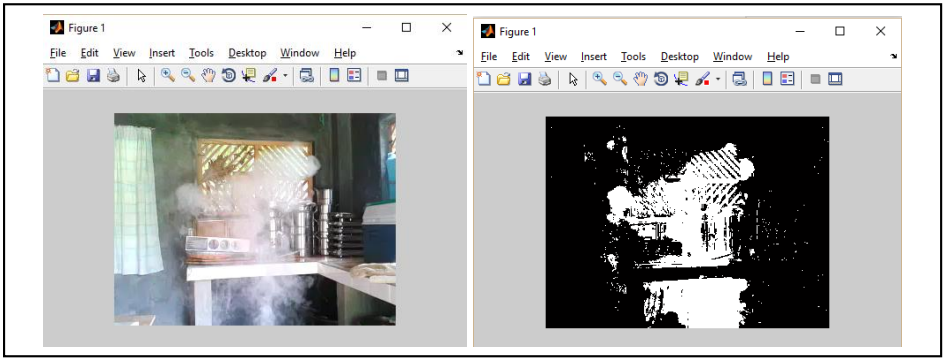

Figure 2. Foreground detection without morphological operations.

As shown in Figure 2, the foreground detection result using GMM (video 1, frame 667) without morphological operations. The left image shows the actual frame of the video, while the right image displays the mask after the foreground detection. The noises and disturbances of the frame are visible in the right image resembling the original background overlapped by the smoke.

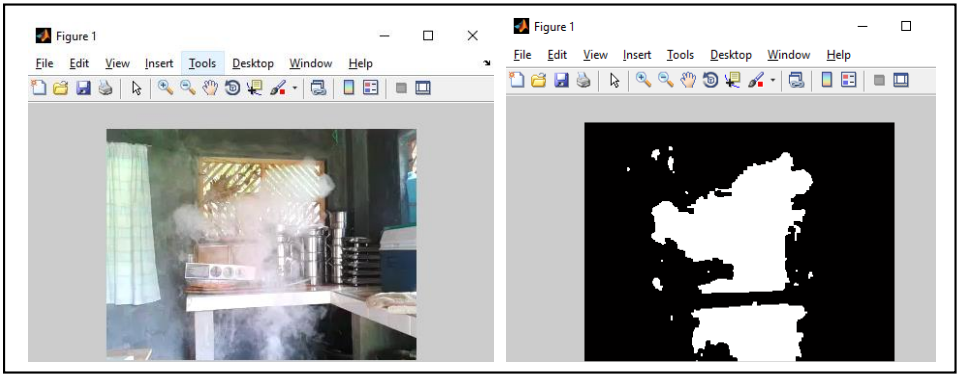

Figure 3. Foreground detection with morphological operations.

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Figure 3, on the other hand, shows the result of the foreground detection applying the morphological operations. Again, the left image shows the actual frame, while the right image displays the detected mask of the smoke after applying morphological operations. The noises and disturbances in the frame's right image are no longer visible since the background considers a static image. In contrast, the foreground considers a moving object.

In extracting the foreground in the video without the morphological operations, the succeeding phases of the motion-based tracking algorithm include the noises. However, the unfiltered noises increased the risk of detecting false objects, which means that the false positive rate or the rate of detection failure also increases, thus affecting the accuracy of the algorithm.

Motion-based Object Tracking

The study used a motion-based object tracking method using a Kalman filter to analyze the motion of the object to verify smoke. The tracking approach tracked each moving object on the video and updated every frame depending on its consistent motion and visibility. Figure 4 and Figure 5 display the motion behavior of objects illustrating the path of both the tracking and the detection of the entire video process. Figure 6, on the other hand, shows the bounding box of the tracking results. The video used for the illustration below is Test Video 1.

Figure 4. Motion tracking and detection plot using Kalmar Filter.

Figure 4 shows the plot of motion-based tracking results using the Kalman Filter for the entire process of the video. The picture includes the path of the tracking results, including both the track when the algorithm follows every motion of the object (red marks) and the track that detects the smoke (black marks).

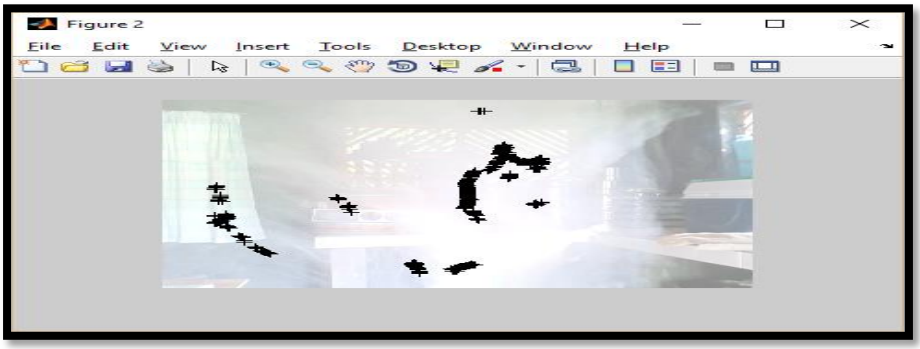

Figure 5. Motion detection plot using Kalman Filter.

Figure 5, similar to Figure 4, solely illustrates the track where it detects the smoke, removing the motion tracking result (red marks) where the Kalman filter analyzed all the moving objects. Further, it shows the

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track (black marks) where the Kalman filter's motion-based detection confirmed that the moving object is smoke.

Figure 6. Display visible tracking result.

Figure 6 (Video 3, frame 314) shows the bounding box of the tracking results after the motion analysis by the Kalman Filter algorithm. The bounding box illustrates a label and a yellow border enclosing the object that appears to be smoke.

Performance Evaluation Test Results

The testing process of the algorithm's efficiency used a set of videos with different characteristics. Each video testing computed the True Positive Rate (TPR) or the correct detection rate, Missing Rate (MR) or the rate of detection failure, and False Positive Rate (FPR) or false detection rate. Table 3 presents the result of the performance evaluation test of the algorithm using the three test videos prepared for each of the five categories also included. Table 4 presents the summary of the results from each category.

Table 3. Performance evaluation results on five test video categories (Video A to Video E).

Test Videos	#frames processed	#frames w/ smoke	#frames w/o smoke	# frames detected w/ smoke	# frames detected w/o smoke	TPR	MR	FPR
				Video A				
Video 1	1316	1016	300	963	0	94.78%	5.22%	0%
Video 2	653	493	160	454	0	92.09%	7.91%	0%
Video 3	533	345	188	318	0	92.17%	7.83%	0%
Average						**93.01%**	**6.99%**	**0%**
				Video B				
Video 1	1301	1083	218	920	0	84.95%	15.05%	0%
Video 2	932	782	150	697	0	89.13%	10.87%	0%
Video 3	863	783	80	705	0	90.04%	9.96%	0%
Average						**88.04%**	**11.96%**	**0%**
				Video C				
Video 1	1480	645	835	533	0	82.64%	17.36%	0%
Video 2	910	630	280	573	0	90.95%	9.05%	0%
Video 3	885	730	155	644	0	88.22%	11.78%	0%
Average						**87.27%**	**12.73%**	**0%**
				Video D				
Video 1	1383	1093	290	686	0	62.76%	37.24%	0%
Video 2	692	507	185	410	0	80.87%	19.13%	0%
Video 3	875	735	140	678	0	92.24%	7.76%	0%
Average						**78.62%**	**21.38%**	**0%**
				Video E				
Video 1	1285	0	1285	0	73	N/A	N/A	5.68%
Video 2	1418	0	1481	0	421	N/A	N/A	29.69%
Video 3	1209	0	1209	0	253	N/A	N/A	20.23%
Average						**N/A**	**N/A**	**18.53%**

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The results show that the algorithm detected a normal smoke having a constant motion with less missing or detection failure rate and no false alarm rate for Test Videos A. This result further implies that the algorithm accurately detected a smoke under a normal condition because the smoke's direction is consistent, and the background is bright enough for the algorithm to distinguish the changing pixels. A normal smoke, described in the study, refers to a well-lighted environment having a smoke in an upward direction at a normal speed.

For Test Videos B, the algorithm detected smoke in a bright environment with a high percentage of correct detection, less rate of detection failure, and no false alarm rate. The detection failure obtained by the algorithm is due to the thin smoke forming at the beginning of the videos. The algorithm considered it already as frames with smoke while the algorithm is still learning the pixels. Furthermore, as the smoke's speed and direction progressed, the algorithm continued learning the motion resulting in its non-detection.

In Test Videos C, the algorithm detected smoke in a dimmer setting with a high percentage of correct detection, less missing rate, and no false alarm rate. However, the darkness of the video, which affects the pixel recognition, increased the detection failure rate of the algorithm. In addition, its inconsistent formation also affects the detection rate. In such cases, there are times that it fades after a formation of thin smoke, resulting in a loss in motion tracking. The algorithm learns the new moving object when the smoke forms again, resulting in its non-detection. This condition of smoke happens in real scenarios.

In the fourth category of the smoke test videos, the algorithm detected a thin smoke. The thin smoke with its corresponding slow-motion contributed to the detection failure rate of the algorithm. This result implies that the algorithm found difficulty in learning the smoke characteristics because of the slowness of the motion and the thinnest of the smoke appearance. Moreover, the smoke adapts the background image resulting in difficulty in the learning process; hence, the higher the detection failure rate.

The three videos in Test Videos E contain no smoke. The algorithm detected objects that appear to be smoke across any environmental circumstances, such as bright and dim environments. This finding arises since the study focused only on studying and tracking the motion of the foreground object, relying on its dynamic characteristics such as movement and disregarding any further trappings such as color threshold and other algorithms for dynamic detection. The algorithm cannot compute the rate of correct detection and detection failure. The formula also relies on the number of real smoke in the video, and the total number of frames detected that these test videos do not have.

Table 4. Performance evaluation result summary.

Test Videos	True Positive Rate (%)	Missing Rate (%)	False Positive Rate (%)
A	93.01	6.99	0
B	88.04	11.96	0
C	87.27	12.73	0
D	78.62	21.38	0
E	NA	NA	18.53
Average	**86.74**	**13.27**	**3.71**

Overall, the algorithm detected smoke early while still forming with a high accuracy rate based on the average percentage of correct detection computed from the test videos prepared. The algorithm also detected smoke with a minimal missing rate and a lesser false alarm percentage. However, it easily detected other non-smoke moving objects on the video in which the algorithm considered their motion as smoke.

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Conclusions and Recommendations

The study focused on detecting smoke using GMM and motion-based detection applying the Kalman filter. These combined approaches detected the smoke in various environmental settings. Although, the dynamic detection using motion-based and Kalman filter detected non-smoke objects in a sample having no smoke since the algorithm focused on detecting moving objects.

However, from the results, the study found an insignificant false detection and detection failure rate after testing several test videos. These numbers are not relatively large compared to the correct detection rate, yet they may adversely affect detection, especially when dealing with more complex situations. However, the study did not explore further due to constraints such as resources and time. Furthermore, since the study only focused on the dynamic characteristic of the smoke, it recommends further research to include color threshold in trapping moving objects; to use some newly introduced techniques in the field of image processing suited to detect smoke comprehensively for better detection and reliable results, or improve those existing algorithms to study smoke's difficult characteristics.

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