Indoor Fire Emergency Evacuation System

GRINO, RENEE ANN F., Ateneo de Davao University
VIDUYA, JAIRAH-MAE H., Ateneo de Davao University

Many buildings already have emergency systems installed, but these systems only provide a warning to unsuspecting victims. In case of an emergency, those people who are not familiar with the building would get lost and are likely more prone to danger. Some instances, the smoke would increase and would cause limited vision for the people who are evacuating the building. With these cases, the indoor emergency evacuation system would guide people to the nearest exit for evacuation. The aim of this study is to have an indoor fire emergency evacuation system that would alert and guide the victims to the nearest evacuation exit in case of a fire emergency. The Indoor Fire Emergency Evacuation System has two subsystems: the real time video-based detection system and the speaker system. The real time video-based detection system (RTVDS) would use CCTV cameras for the video input that would then be processed through computer vision algorithms such as edge detection, color detection, motion detection, and area dispersion for fire and smoke detection. The RTVDS will be integrated with the speaker system, once the RTVDS detects fire and smoke, the speaker system would then be the guide of the victims to the nearest emergency evacuation system.

General Terms: Computer Vision, Motion Detection, Fire Detection, Smoke Detection, Video-Based Detection, Emergency Evacuation, Edge Detection, Color Detection, Area Dispersion, Motion Segmentation, Background Subtraction, Optical Flow

Additional Key Words and Phrases: evacuation, fire emergency, emergency, indoor emergency system

1. INTRODUCTION

1.1 Background of the Study

Every year, hundreds of structure fires destroy property and hurt people. In 2014, according to the Philippine Daily Inquirer, there is a total of 646 structural fire reported (Gamil, 2015). Many buildings have their own fire detection system such as smoke detectors and heat detectors. These systems work well at only providing warning to unsuspecting victims, but it does not give the victims directions to where the nearest emergency exits are.

There are many indoor emergency evacuation systems developed over the years, but most of them involves using hand held devices. In case of fire, one of the rules is to leave all of your personal belongings; bringing your hand held devices would be the least of your worries in case of an emergency. Thus, these mobile emergency evacuation systems would be pointless.

This project will focus on the integration of a real time video-based detection system and a speaker system. In a fire emergency, human vision would be limited due to increasing smoke inside a building, however with the use of computer vision algorithms, we can achieve a system that could detect fire and smoke like a human would. Once fire is detected on a certain area, a speaker system would then output directions to an alternative nearest exit for the victims. If there is no risk of danger, the speaker system would then output its original nearest exit directions.

1.2 Problem Statement

The main problem of the study is how to integrate a real time video-based detection system and a speaker system that would alert and guide the victims to the nearest evacuation exit in case of a fire emergency.

The specific problems of the study are as follows:

(1) How would the two systems alert the people for an evacuation?

(2) How would the system detect fire through video input?

(3) How would the speaker system direct the victims out of the building?

(4) What are the algorithms to be used in detecting fire and smoke?

(5) When would the system alert the victims to take an alternative exit instead of the main exit?

(6) What is the algorithm to be used to find alternative nearest exit when the original exit cannot be accessible?

1.3 Objectives

The main objective of the study is to integrate a real time video-based detection system and a speaker system that would alert and guide the victims to the nearest evacuation exit in case of a fire emergency.

The specific objectives of the study are as follows:

1 Explain how the real time video-based detection system alert and guide would people for an evacuation.

2 Explain how the system detect fire through video input.

3 Explain how the speaker system direct the victims out of the building.

4 Identify what algorithms to be used in detecting fire and smoke.

5 Explain when the system would alert the victims to take an alternative exit instead of the main exit.

6 Identify what algorithm to be used to find an alternative nearest exit when the original exit cannot be accessible.

1.4 Significance of the Study

Many buildings already have emergency systems installed, but these systems only provide a warning to unsuspecting victims. In case of an emergency, those people who are not familiar with the building would get lost and are likely more prone to danger. Some instances, the smoke would increase and would cause limited vision for the people who are evacuating the building.

With these cases, the indoor emergency evacuation system would guide people to the nearest exit for evacuation. The indoor emergency evacuation system consists of two subsystems: the real time video-based detection system which uses CCTV cameras to detect fire, and the speakers system which will be the guide for evacuation.

1.5 Scope and Limitations

The indoor emergency evacuation system covers fire detection and evacuation guide. The system is consists of two subsystems: the real time video-based detection system and the speakers system. The real time vide-based detection system will use CCTV cameras to detect fire in the area that it was assigned to, and the speakers system would be the guide for evacuation once the detection system alerts that there is fire in the area.

This indoor evacuation system has its limitations. In real time video-based detection system, the CCTV cameras should be in stationary angle. Also, the number of CCTV Cameras and Speakers would matter, for instance, when the building has CCTV Cameras and emergency speakers already installed, the view for the video-based detection system would be limited. In speakers system, the speakers should be nearby the CCTV cameras for they operate in pair, the cameras detect fire and the speakers are guide for evacuation.

The fire detection system does not detect very small fire. There are instances that the system detects the light/glare, but this rarely happens.

The smoke detection includes white areas of the video, which may output false alarm.

The proponents were able to detect smoke in a video, but they were not able to use Feature Extraction algorithms due to lack of functions in MATLAB.

2. REVIEW OF RELATED LITERATURE

2.1 Real Time Fire Detection in Low Quality Video

In 2010, Nicholas James True from University of California, San Diego, created a robust algorithm for detecting fire in low quality video data. He used Video-Based Fire Detection (VBFD) systems with the use of color classification algorithm and motion detection algorithm, it can detect fire at small or large distances and they can sound the alarm in as little time as it takes to process the input video.

The color classification algorithm would detect the fire only by using color, but the color of fire would change drastically depending on the amount of ambient light and the intensity of light sources in the scene, and this is where the motion detection algorithm comes in. The motion detection algorithm is used to detect the fire-colored moving objects in the region of interest (RIO). But fire behavior seems completely unpredictable. However, by closer inspection reveals that there is a pattern hidden in fire's chaotic behavior: there is much more motion near the top and sides of a fire and then near the base. He used the edge motion algorithm to detect the flame flicker motion of fire (True, 2009).

.

True's study was quite good, however there are various drawbacks for this system: Color detection is always hostage to variations in lighting conditions and fast motion detection algorithms lack the specificity necessary to differentiate motion from lighting changes. Another drawback for this fire detection algorithm is the fact that the cameras that capture the input data need to be completely stationary. The motion detection algorithms rely on the camera to be stationary since they don't have any understanding of the scene that they capture and they don't track any objects in the scene. Lastly, he was not able to incorporate smoke detection capabilities in his work.

2.2 Optimized Flame Detection Using Image Processing Based Technique

Another approach was done by Yadav et al. in 2012. They created an optimized system to detect an occurrence of fire based on video images. In this project the authors used previously proposed methods (edge detection, color detection, and motion detection) to conduct the fire detection and propose new techniques to implement in parallel.

In developing their system the following stages are involved:

- Edge detection
  They used the edge detection
- Proposed algorithm
  - Motion Detection
  - Gray-cycle pixel detection
  - Area dispersion

2.2.1 Edge Detection

The edge detection can be used to analyze color detection of fire. The edge detection system compares the intensity difference in the image and provides an image with black and white color space where high intensity area is filled with white and low intensity area is filled with black color (Yadav, et al, 2012).

Figure 1 describes the block diagram of Edge Detection model used in Yadav's study:

Figure 1 Edge Detection Model

2.2.2 Motion Detection

The motion detection is used to detect any occurrences of movement in a sample video (Yadav et al., 2012). In their system, they took two sequential images from video frames. After applying the two methods edge detection and color detection, they get probable area of fire pixel and compare the RGB value to of frame1 and frame 2 for corresponding pixel and if pixel value differs. The motion detection will show motion and will give resultant output to the operator.

Figure 2 describes the block diagram of Motion Detection model used in Yadav's study:

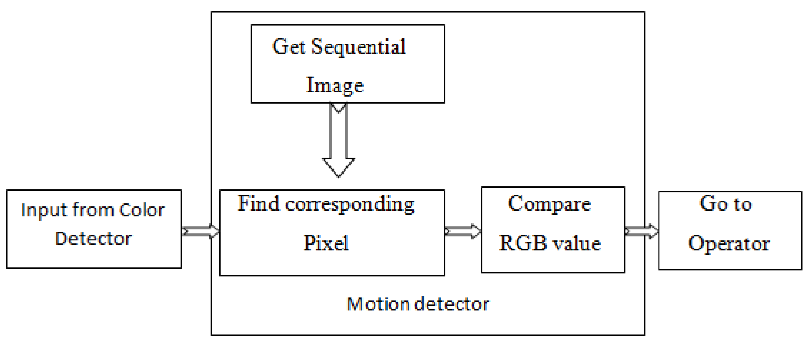


Figure 2 Motion Detection Model

2.2.3 Gray-cycle Pixel Detection

The gray scale pixel detection is used to detect occurrences of smoke pixel in the selected area which is half above the area, detected by color direction method (Yadav et al, 2012). The method they used to apply on the area (Probabilities Quintiles and Random Samples) and the area of the fire pixel which they get from the edge and color detection method. Gray-cycle pixel have some properties in terms of RGB. This method will check these properties inside this area (PQRS) and then provide result to the operator.

Figure 3 describes the block diagram of Gray-cycle Pixel Detection model used in Yadav's study:

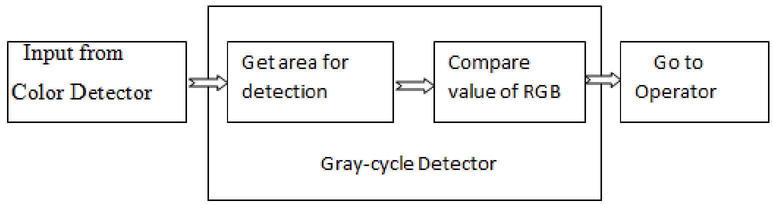


Figure 3 Gray-cycle Pixel Detection Model

2.2.4 **Area Detection**

Area detection method is used to detect dispersion of fire pixel area in the sequential frames (Yadav et al, 2012). In this method, they took two sequential images which comes out from the color detector when we check dispersion in minimum and maximum coordinate of X and Y axis, acquired from color detector. This method compares fire pixel area of two sequential frames on the basis of minimum value of x & y and maximum value of x & y. In case of fire, if any extreme value of x and y axis will increase for next frame, then there is area dispersion takes place and the system will provide output to the operator.

Figure 4 describes the block diagram of Area Detection model used in Yadav's study:

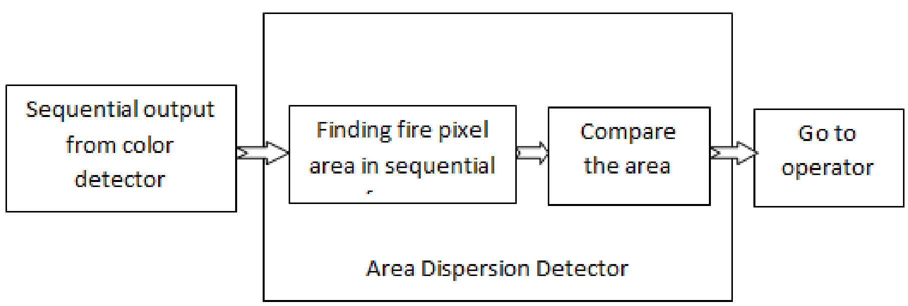


Figure 4 Area Detection Model

Their fire detection system gave a better performance in terms of less false alarm and thus a higher system performance is achieved. Moreover, the system is more reliable in reefing the result comes out from existing detection methods. For smoke detection, they mentioned using gray-cycle, however, it was only a proponent for proving that the object detected for their fire detection system was actually a real fire. Their study's scope did not further explore the capabilities of detecting smoke alone.

2.3 Smoke Detection using Spatial and Temporal Analyses

Lee et al. (2011) proposed a novel smoke-detection approach using spatial and temporal analyses, based on the block-processing technique. They developed an algorithm for detecting movement object by combining background subtraction and temporal difference.

"*This method analyzes energy-based and color-based features within the spatial, temporal, and spatial-temporal domains, before all the proposed features are combined using an SVM classifier.* (Lee et al., 2011)"

2.3.1 Candidate Region Extraction

The candidate smoke region extraction process was made possible by analyzing the spatial and temporal characteristics of video sequences for the features (2D Spatial Wavelet Analysis, 1D Temporal Energy Analysis, and 1D Temporal Chromatic Configuration Analysis) (Lee et al., 2011).

Figure 5 depicts the process of Foreground Segmentation using Background Subtraction based on the study of Lee, et al. (2011):

Figure 5 Foreground Segmentation using Background Subtraction (GMM).

After the foreground segmentation approach, the block-based technique was used in tracking the smoke targets since the smoke regions may continuously appear and disappear. The block-based technique is depicted in Figure 6, which shows that only background subtraction values and temporal differences larger than the predefined thresholds are regarded as candidates containing moving objects, which reduces computational cost (Lee et al., 2011).

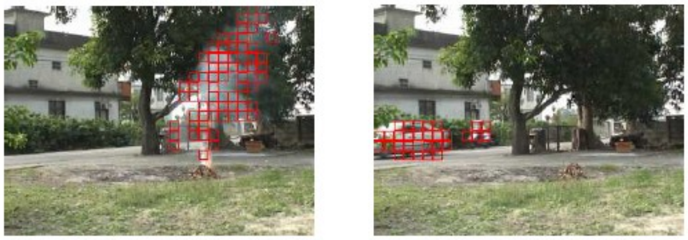


Figure 6 Result of Block Processing

2.3.2 Feature Extraction

In the Feature Extraction, the three features were merged, namely:

1. 2D Spatial Wavelet Analysis – Since smoke is semi-transparent, the edges of image frames may lose their sharpness, leading to the decrease in high-frequency content of an image. (Lee et al., 2011) Using a spatial wavelet transform of the current and background image, smoke in the scene was identified by estimating the background and monitoring the decrease in high-frequency energy.
2. 1D Spatial-Temporal Energy Analysis – In the early stages of fire, smoke is semi-transparent, and eventually becomes less visible as time passes. The high-band (details) and low-band (approximations) information can be obtained by applying the 1D Wavelet Transformation to the signal S.
3. 1D-Temporal Chromatic Configuration Analysis – Color information was the third characteristic in identifying smoke in a video. When the smoke starts to expand, the chrominance values of pixels decreases, which provides another sign that may differentiate smoke from moving objects.

Figure 7 shows the comparison of energy analysis for ordinary moving objects and smoke (Lee et al, 2011).

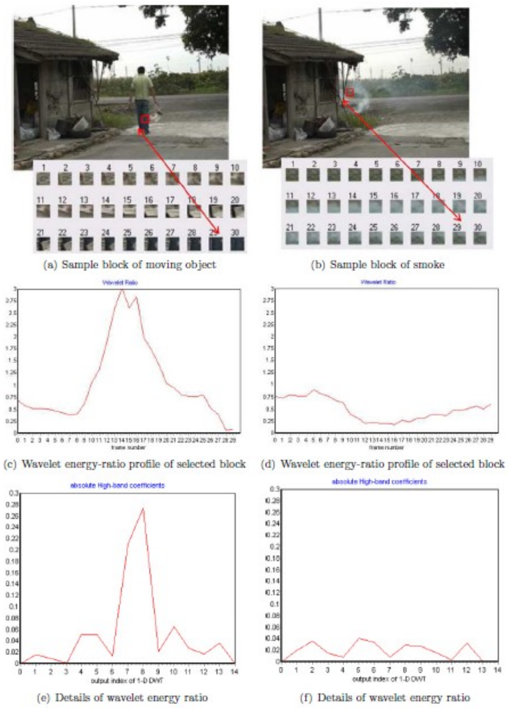


Figure 7. Comparison of energy analysis for ordinary moving objects and smoke

2.3.3 **Classification and Verification**

The three features are then combined as a feature vector for each candidate block before they get classified using a Support Vector Machine. Their proposed system used LIBSVM tools to train the classifier for smoke detection. The classified blocks retrieved from a moving object were submitted to the next stage where the connected blocks were labeled before they were verified.

Lee et al.'s (2011) Smoke Detection system may be used for our research paper since it was able to produce favorable results from different situations (e.g. smoke in a room, cars in a tunnel during day/night time, pedestrians walking through smoke, etc.). It was compared on the individual features listed, and though its detection rate was lower than the three features, its false detection rate was higher than the three features by combining the three features, and adding the ADU, which makes it reliable for smoke detection.

2.4 Theoretical Framework

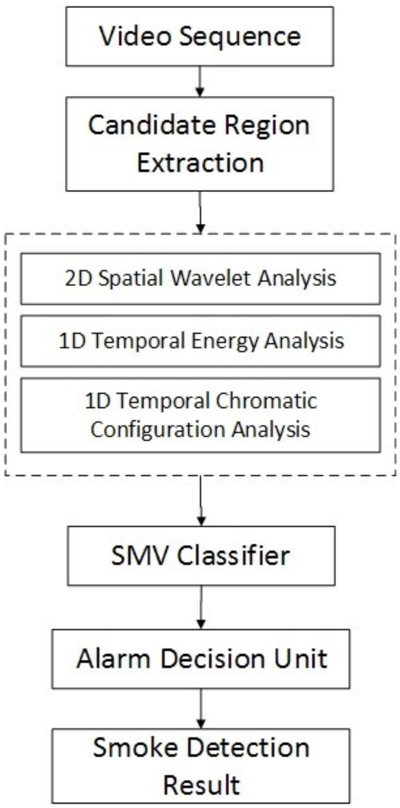


Figure 8 Theoretical Framework (Smoke Detection)

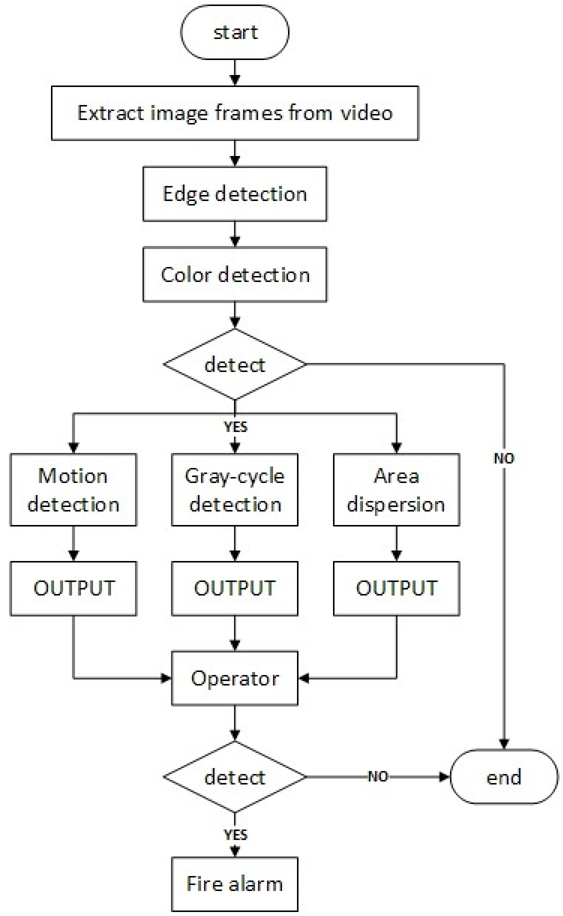


Figure 9 Theoretical Framework (Fire Detection)

Figures 8 and 9 describes the theoretical framework of the study for fire detection and smoke detection systems. Figure 5 depicts a theoretical framework of smoke detection system based on the research led by Lee, et al. (2011). Figure 6 is a theoretical framework of a real time video-based fire detection studied by Yadav, et al. (2012).

3. METHODOLOGY

3.1 CONCEPTUAL FRAMEWORK

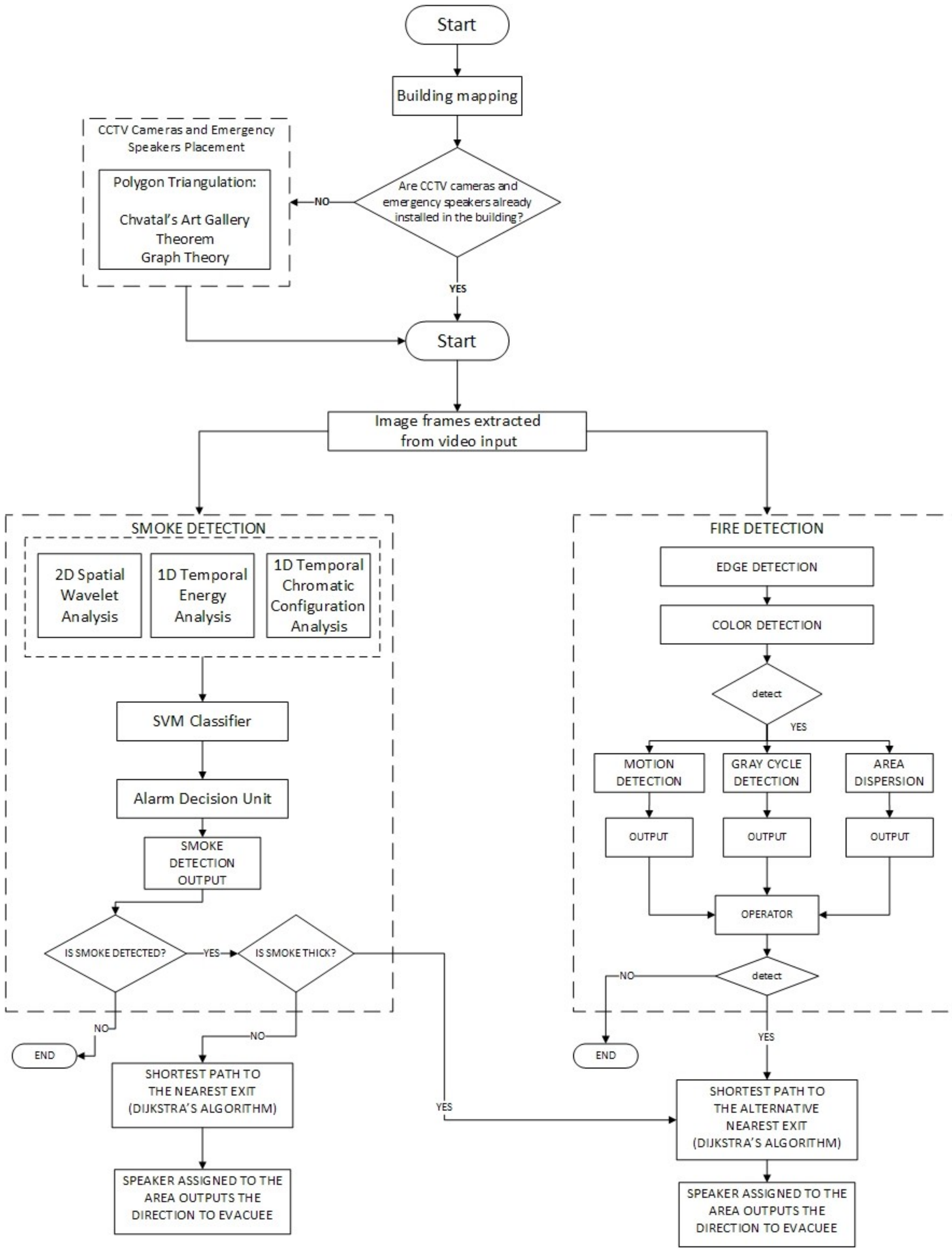


Figure 10. Conceptual Framework (Indoor Fire Emergency Evacuation System

3.2 METHODOLOGY

3.2.1 Building Mapping

The proponents will map buildings by nodes (for hallway paths, intersections, exits), and connect them, with the main exit programmed. When the source of danger is nearby, the node will be eliminated, and the system will generate the alternative nearest exit, and direct the evacuees there.

3.2.2 Placement of CCTV and Emergency Speakers

When there are no speakers or CCTV cameras placed inside the building, the proponents will use Polygon Triangulation in solving where the CCTV and Speakers should be placed.

3.2.3 Smoke Detection and Fire Detection Algorithm

The proponents will use the image frames extracted from the video input and proceed with the Smoke Detection and Fire Detection algorithms.

3.2.4 Shortest Path

The proponents will use Dijkstra's algorithm in looking for different shortest exit paths in the building.

3.2.5 Direction Output

If smoke is detected, and smoke is thin, the speaker will direct the evacuees to the nearest exit from his or her position. If smoke is thick, and there is fire, the speaker will direct the evacuees to an alternative exit path.

3.2.5.1 Speakers

The proponents will use networks of speakers within the building, either one applier with multiple speakers or the speakers has their own built-in amplifiers. Through these speakers, the proponents will be able to adjust its amplitude so that it will only be heard in a certain area where a certain speaker will be placed, thus the direction output from each speakers will not be overlapped with the others.

4. EVALUATION

The proposed methods are implemented in two laptops with Windows 10 Pro operating system, 64-bit system type, Intel(R) Core(TM) i3-3110M CPU @ 2.40GHz processor, and 4.00 GB installed memory (RAM) and with a Windows 8.1 Operating System, 64-bit system type, Intel(R) Core(TM) i3-4030U CPU @ 1.90GHz processor, and 4.00GB installed memory (RAM). It is then tested offline videos containing only fire, only smoke, both fire and smoke, and videos with no smoke or flame.

4.1 MAPPING WITH CCTV PLACEMENTS

Figure 11: A simple map of a one floor building.

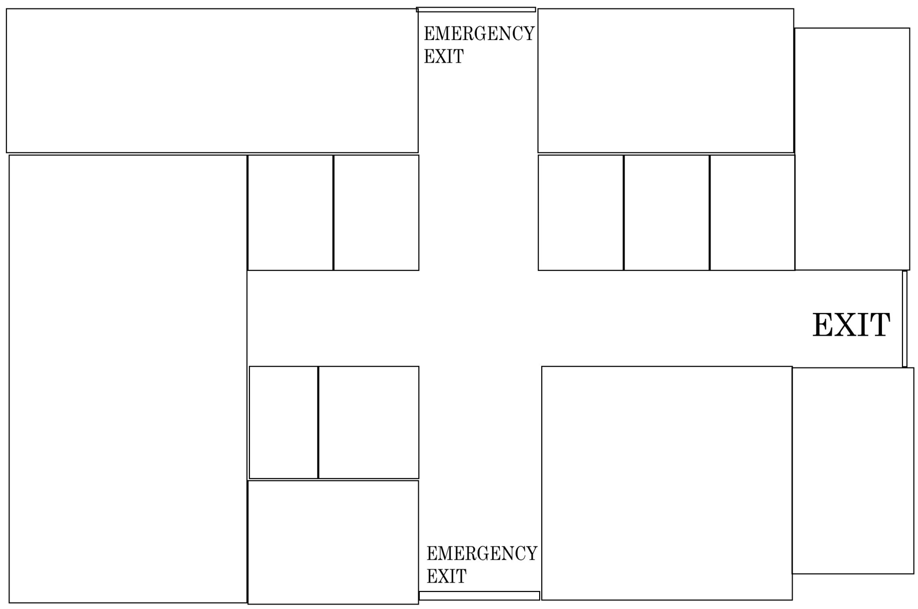
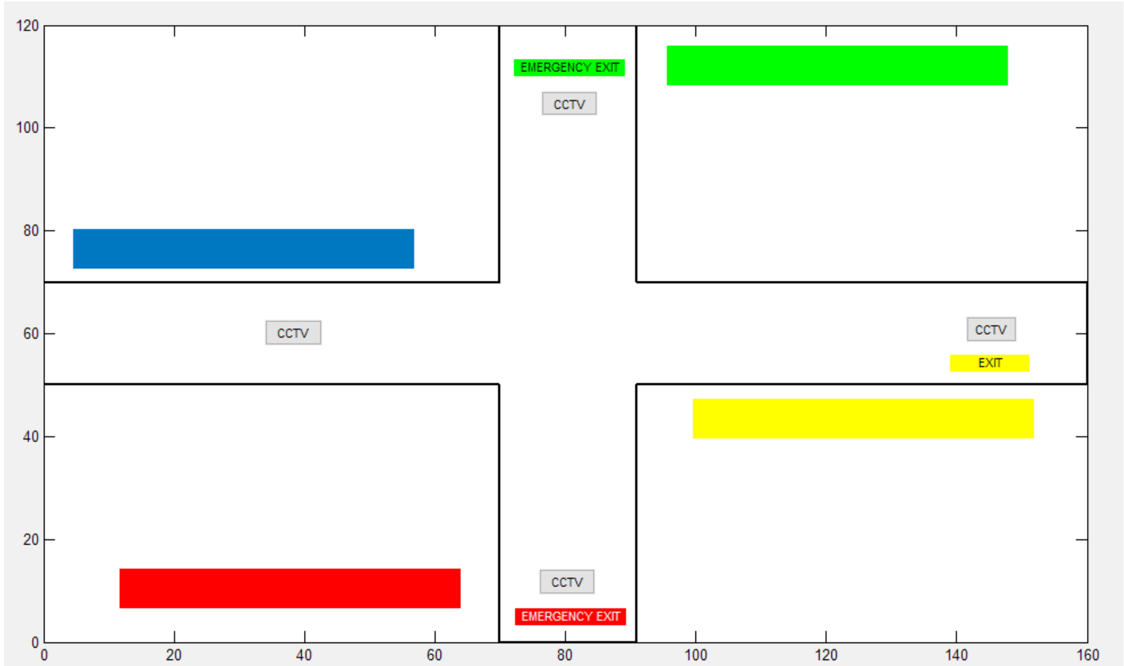


Figure 12: The MATLAB



version of Figure 11 with color coding for the exits.

4.2 FIRE DETECTION SYSTEM

Motion detection

Figure 13

Figure 14

Figure 13 shows the original frame of the input video and Figure 14 shows the masked frame with only the moving pixels are extracted (the white area).

Edge detection and Color detection

Figure 15 *Figure 16*

Figure 15 shows the original frame extracted from the video input and Figure 16 shows the edge detection and color detection. The edge detection finds the edges in intensity image, and the color detection with specific fire color values, fills out the edges with white area.

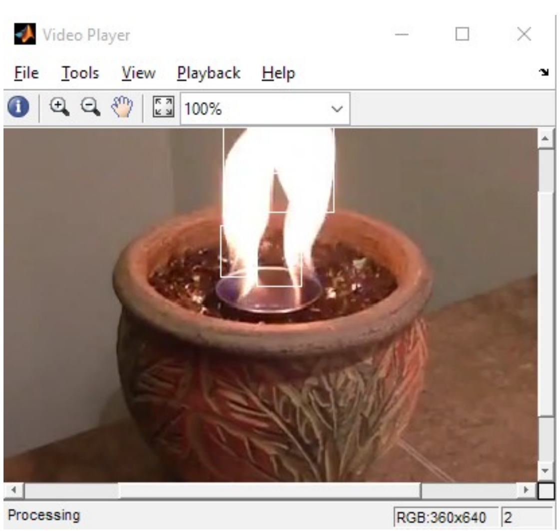
Area Dispersion and Gray-cycle Detection

Figure 16

Figure 17

Figure 16 shoes the filled area with edge detection and color detection. Figure 17 shows the area dispersion and gray-cycle detection. The area dispersion and gray-cycle detection fills out the possible fire pixels and smoothens the edges.

Fire Detection System Output



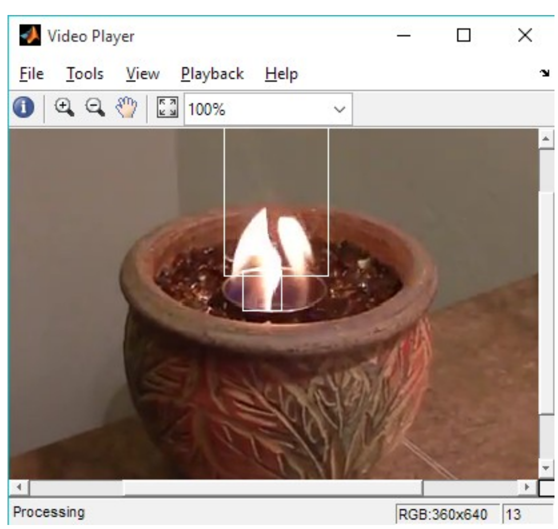
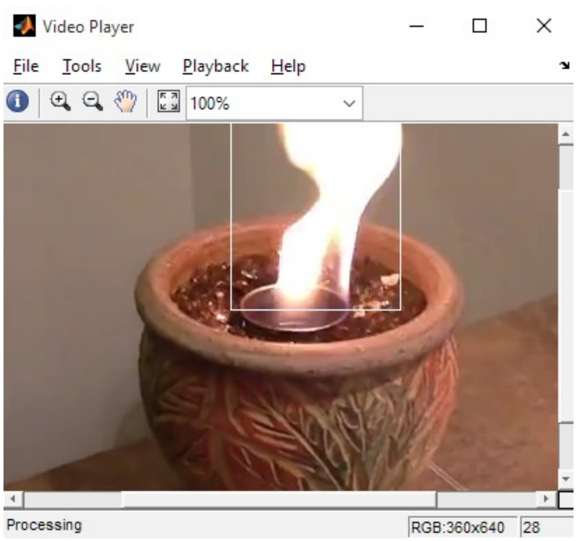


Figure 18 *Figure 19*



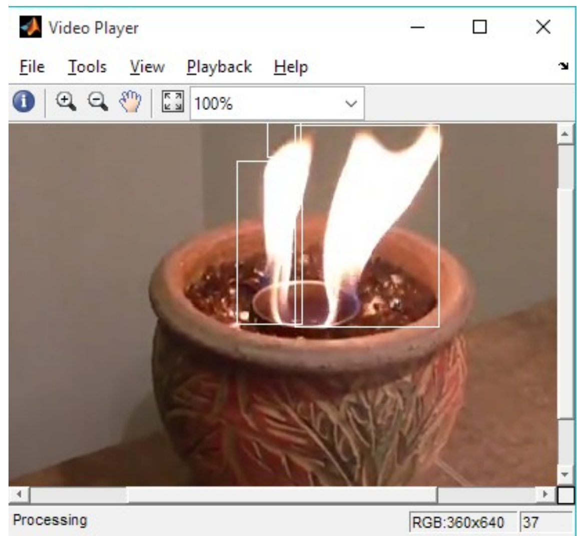


Figure 20 *Figure 21*

Figures 18-21 shows the unmasked fire detection output.

4.3 SMOKE DETECTION

Figure 22

Figure 23

Figure 22 and 23 show the masked part of smoke.

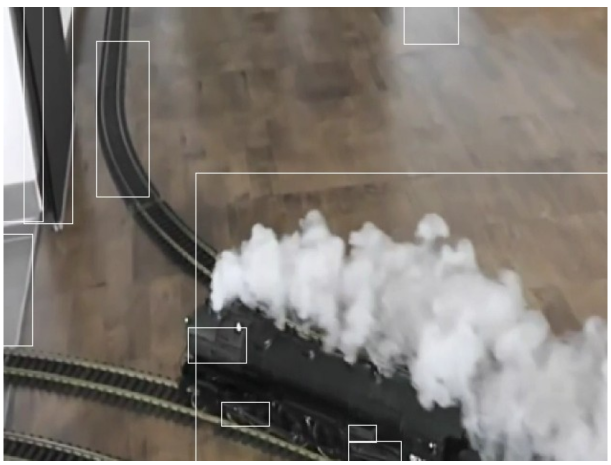


Figure 24

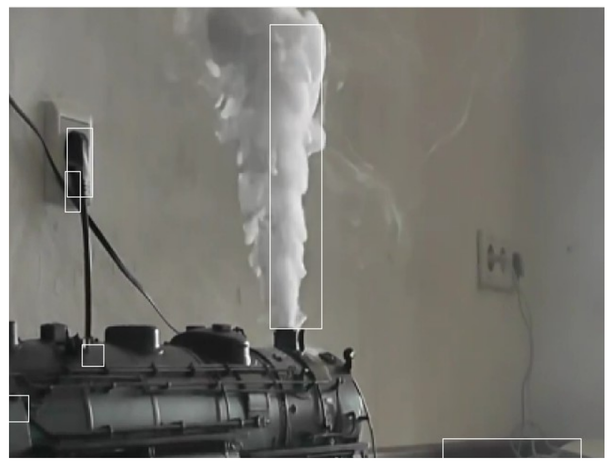


Figure 25

Figure 24 and 25 show the unmasked smoke detection output.

4.3 SHORTEST PATH AND DIRECTION OUTPUT

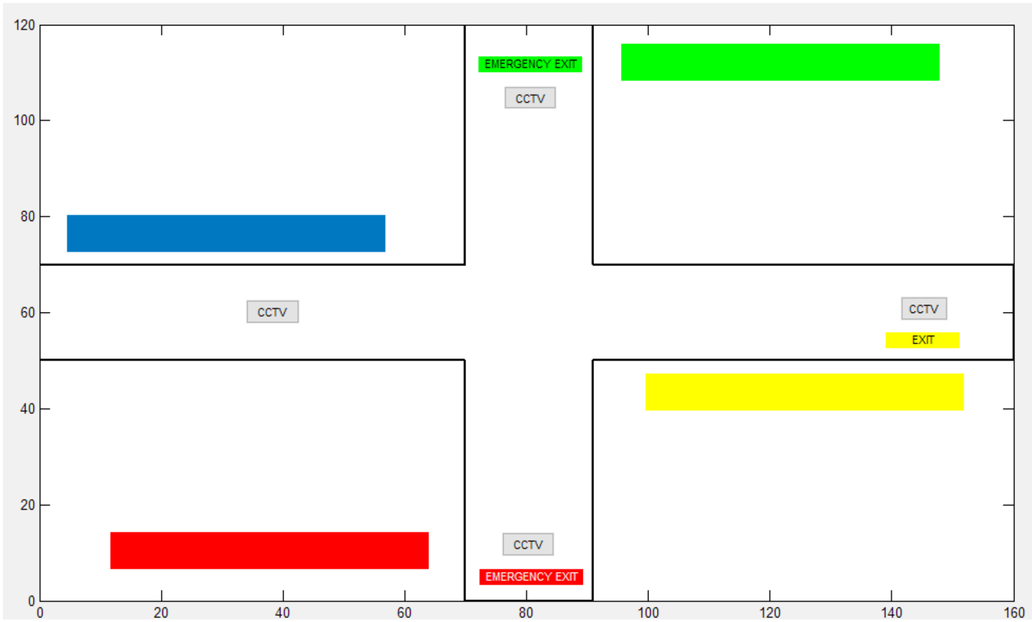


Figure 26: color coded map.

Figure 26 shows the color coded map of Figure 11. The colored rectangle boxes serves as the output direction from the emergency speakers.

Table 1: GREEN EXIT IS NOT AVAILABLE		
TRIALS	**POSSIBLE EXIT**	**MINIMUM COST TIME**
Trial 1	Blue to Red	0.118394 seconds.
	Blue to Yellow	0.108049 seconds.
Trial 2	Blue to Red	0.113834 seconds.
	Blue to Yellow	0.109258 seconds.
Trial 3	Blue to Red	0.115177 seconds.
	Blue to Yellow	0.109919 seconds.
Trial 4	Blue to Red	0.115493 seconds.
	Blue to Yellow	0.108747 seconds.
Trial 5	Blue to Red	0.116160 seconds.
	Blue to Yellow	0.111350 seconds.

Table 1 presents data from five different trials of elapsed time to a certain available exit if the green exit is not available or detected a fire from its area.

Getting the average minimum cost time of a possible exit we use the mean equation:

$$\mu = \frac{\sum x}{n}$$

Where:
μ = average;
$\sum x$ = sum of values;
n = number of trials;

Solving the average minimum cost time of Blue to Red:

$$\mu = \frac{\sum BR}{n}$$

$$\mu = \frac{0.118394 + 0.113834 + 0.115177 + 0.115493 + 0.116160}{5}$$

Average time of Blue Station to Red Exit is = 0.115812 seconds.

Solving the average minimum cost time of Blue to Yellow:

$$\mu = \frac{\sum BY}{n}$$

$$\mu = \frac{0.108049 + 0.109258 + 0.109919 + 0.108747 + 0.111350}{5}$$

Average time of Blue Station to Yellow Exit is = 0.109465 seconds.

∴The quickest way for exit is to Yellow Exit if the Green Exit is not available.

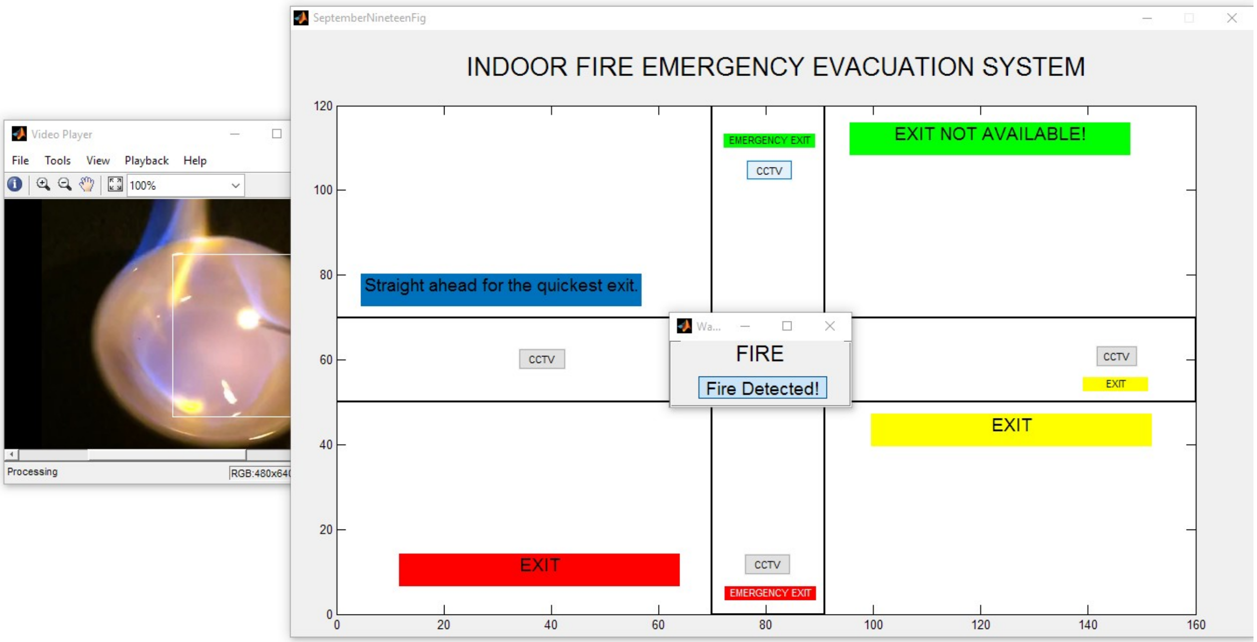


Figure 27

Figure 27 shows the output of the system if fire is detected in the green exit area.

Table 2: YELLOW EXIT IS NOT AVAILABLE		
TRIALS	**POSSIBLE EXIT**	**MINIMUM COST TIME**

Trial 1	Blue to Red	0.111185 seconds.
	Blue to Green	0.110853 seconds.
Trial 2	Blue to Red	0.112588 seconds
	Blue to Green	0.111527 seconds.
Trial 3	Blue to Red	0.113671 seconds.
	Blue to Green	0.113335 seconds.
Trial 4	Blue to Red	0.116945 seconds.
	Blue to Green	0.111236 seconds.
Trial 5	Blue to Red	0.113174 seconds.
	Blue to Green	0.109826 seconds.

Table 2 presents data from five different trials of elapsed time to a certain available exit if the yellow exit is not available or detected a fire from its area.

Solving the average minimum cost time of Blue to Red:

$$\mu = \frac{\sum BR}{n}$$

$$\mu = \frac{0.111185 + 0.112588 + 0.113671 + 0.116945 + 0.113174}{5}$$

Average time of Blue Station to Red Exit is = 0.113646 seconds.

Solving the average minimum cost time of Blue to Green:

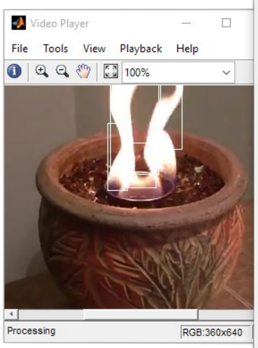
$$\mu = \frac{\sum BG}{n}$$

$$\mu = \frac{0.110853 + 0.111527 + 0.113335 + 0.111236 + 0.109826}{5}$$

Average time of Blue Station to Green Exit is = 0.111355 seconds.

∴The quickest way for exit is to the Green Exit if the Yellow Exit is not available.

Figure 28



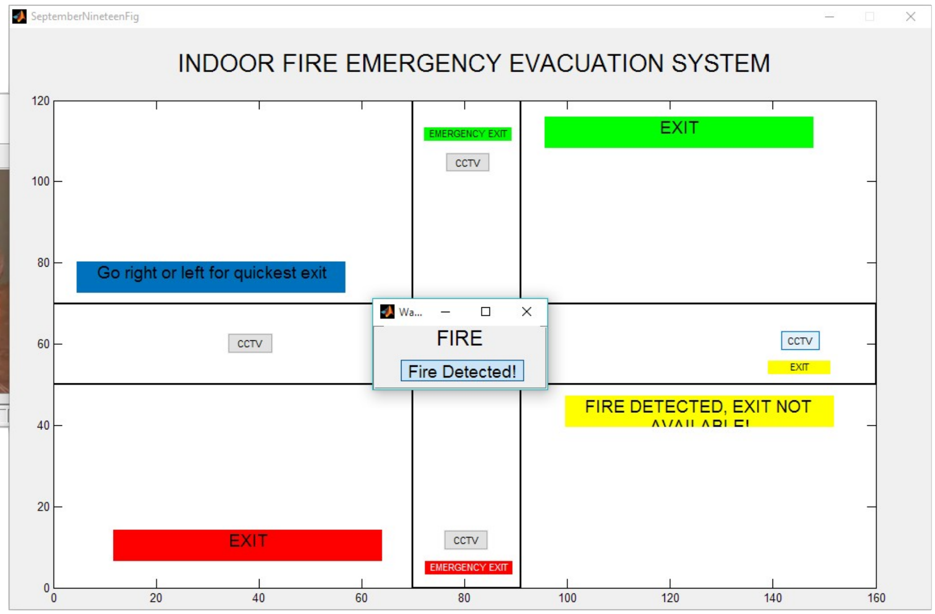


Figure 28 shows the output of the system if fire is detected in the yellow exit area.

Table 3: RED EXIT IS NOT AVAILABLE		
TRIALS	**POSSIBLE EXIT**	**MINIMUM COST TIME**
Trial 1	Blue to Yellow	0.140863 seconds.
	Blue to Green	0.131735 seconds.
Trial 2	Blue to Yellow	0.111452 seconds.
	Blue to Green	0.110819 seconds.
Trial 3	Blue to Yellow	0.116311 seconds.
	Blue to Green	0.110801 seconds.
Trial 4	Blue to Yellow	0.116145 seconds.
	Blue to Green	0.109674 seconds.
Trial 5	Blue to Yellow	0.109484 seconds.
	Blue to Green	0.111215 seconds.

Table 3 presents data from five different trials of elapsed time to a certain available exit if the red exit is not available or detected a fire from its area.

Solving the average minimum cost time of Blue to Yellow:

$$\mu = \frac{\sum BY}{n}$$

$$\mu = \frac{0.140863 + 0.111452 + 0.116311 + 0.116145 + 0.109484}{5}$$

Average time of Blue Station to Yellow Exit is = 0.118851 seconds.

Solving the average minimum cost time of Blue to Green:

$$\mu = \frac{\sum BG}{n}$$

$$\mu = \frac{0.131735 + 0.110819 + 0.110801 + 0.109674 + 0.111215}{5}$$

Average time of Blue Station to Green Exit is = 0.114849 seconds.

∴The quickest way for exit is to the Green Exit if the Red Exit is not available.

Figure 29

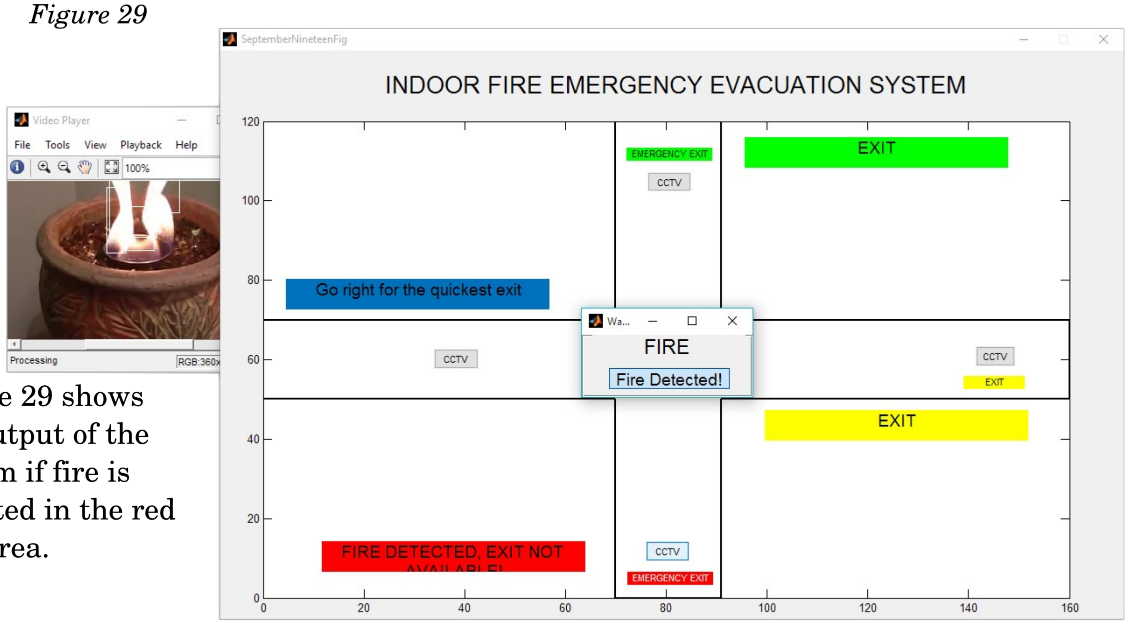
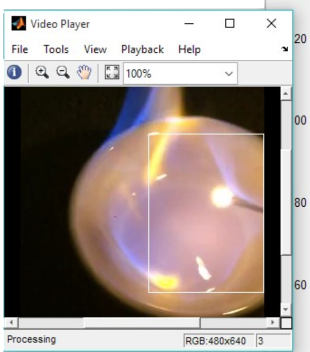


Figure 29 shows the output of the system if fire is detected in the red exit area.

Figure 30



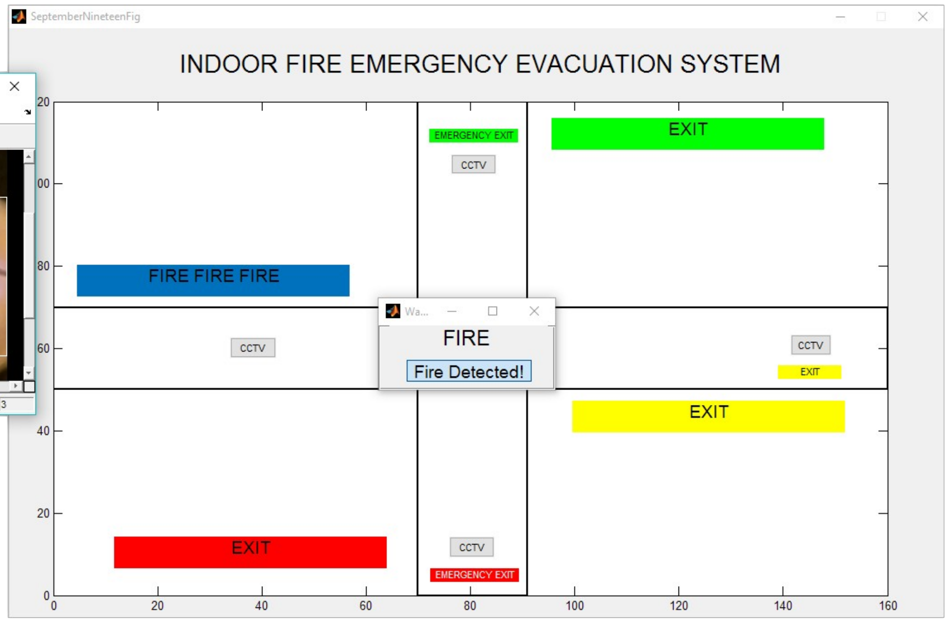


Figure 30 shows the output of the system if fire is detected in the blue area.

Video Inputs	Description	FIRE/SMOKE DETECTED
Video 1	How to make a DIY indoor fire pit	1
Video 2	Custom indoor-out door fire pit	1 | x
Video 3	Safe indoor fire pit	1 | x
Video 4	Flaming detergent foam	1 | x
Video 5	Indoor g scale Hudson smoking	1 | 1
Video 6	(No fire or smoke) Earthquake 7.2 magnitude hit Cebu CCTV captured cam4 (Oct.15, 2013)	0 | x
Video 7	(No fire or smoke) CCTV camera of a hospital hallway	0 |x
Video 8	(no fire or smoke) Two people in a hallway	0 | x
Video 9	Smoke bomb in a kitchen	0 | x

Table 4 presents 9 video data used for evaluation.

5. CONCLUSION AND FUTURE WORK

Using edge detection, color detection, motion detection, area dispersion, and gray-cycle detection algorithms helped in detecting fire in a video. Comparing the color pixels for Smoke was not enough to accurately identify smoky areas, because this may trigger false alarms. For future work, the smoke and fire detection should be implemented as one. For smoke detection, more new approach or methods should be considered. Approaches or methods for smoke detection through video input is still developing for there are many smoke-like that might still be included in a smoke detections systems e.g. (fog, steam).

Brovko, N., Bogush, R., & Ablameyko, S. (2013). Smoke detection algorithm for intelligent video surveillance system, *21*(1), 142–156.

Edington, C. (2014). Comparing Different Visual Motion Detection Algorithms New Mexico Supercomputing Challenge Final Report Team Members :

Gamil, J. T. (2015). No Title.

Kubba, S. (2012). Handbook of Green Building Design and Construction. *Handbook of Green Building Design and Construction*. doi:10.1016/B978-0-12-385128-4.00005-6

Lee, C.-Y., Lee, C.-T., Hong, C.-T., & Su, M.-T. (2012). SMOKE DETECTION USING SPATIAL AND TEMPORAL ANALYSES Received March 2011 ; revised September 2011 1 . Introduction . Numerous fires threaten human lives and property throughout the world every day ; thus , there is a need for a reliable fire-detection tech, *8*(6), 1–11.

Piccardi, M. (2004). Background subtraction techniques: a review. *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No.04CH37583)*, *4*, 3099–3104. doi:10.1109/ICSMC.2004.1400815

Porteous, R. (2011). Heat Detectors - Principle of Operation.

True, N. J. (2009). Electronic Theses and Dissertations.

Walker, S. (2012). No Title.

Yadav, G., Gupta, V., & Gaur, V. (2012). Optimized Flame Detection Using Image Processing Based. *Indian Journal of Computer Science and Engineering (IJCSE)*, *3*(2), 202–211.

Kim, D., & Wang, Y. F. (2009). Smoke detection in video. *2009 WRI World Congress on Computer Science and Information Engineering, CSIE 2009*, *5*, 759–763. doi:10.1109/CSIE.2009.494