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A FUZZY-BASED SMOKE DETECTION ON EMBEDDED SYSTEM

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ABSTRACT

This paper proposes a new method for smoke detection based on the characteristic of color and movement of the video obtained from a static camera. Firstly, background subtraction algorithm is used to detect the motion and distinguish between motion and non-motion object on each frame. Secondly, color of each pixel of the moving regions is checked and compared with the typical of color of smoke such as gray, white and black. Thirdly, because smoke has rapid growth as soon as it formed, this paper calculates the growth rate of the moving regions. Finally, a fuzzy logic system is developed to process all previous results. Output threshold of the fuzzy system can be adjusted to adapt to environment conditions. The proposed method is implemented on embedded system to ensure execution speed in real-time, so we can develop future applications such as integrating into the surveillance camera, building a firefighting robot and so on. Experimental results on different videos in different environments show that the proposed method is very effective and achieves high accuracy in the detection of smoke.

Keywords: *Smoke Detection, Image Processing, Computer Vision, Fuzzy Logic System, Embedded system*

1. INTRODUCTION

Fire is one of the most common disaster that caused significant losses to humanity and environment. Early detection of fire can help to prevent the fire before it grows too large. Nowadays, people are interested in intelligent fire alarm system capable of detecting fires as soon as it formed. Detecting smoke is the best way help to detect fire early. There are different types of smoke detectors such as optical smoke detectors, ionization smoke detectors, air sampling smoke detectors and so on. These smoke detectors are expensive to setup and can be only used in closed space. Furthermore, because these smoke detectors require a large enough smoke to affect system, they may not suit for early detecting of fire. With the rapid development in digital image processing technology [16], there are many advantages of replacing the conventional smoke detector with smoke detection system based on computer vision. A smoke detection system based on computer vision can detect smoke in open space. Furthermore, this system is easy to operate and control with low cost.

Recently, many researchers have developed algorithms for smoke detection based on image processing [1-15]. In [1], optical flow was used to calculate the movement region to extract smoke. This approach is highly sensitive to noise. In [8], the authors proposed an accumulated model of block motion orientation to realize real-time smoke detection. This model can mostly eliminate the disturbance of artificial lights and non-smoke moving objects. In [9], a wavelet transform was applied to get the total energy of each frame and then the area of decreased high frequency energy component was identified as smoke. However, the change of light in the environment may falsify information on the energy component. Yuan, et al. [10] used variants of LBPs to propose a video-based smoke detection with histogram sequences of LBP and LBPV pyramids. In [11], a modified CS-LTP descriptor was proposed to describe the texture changed by smoke effect. With the background modeling, the blocks of smoke region candidates are extracted and then further verified by examining their colors. This approach can detect gray, white and black smoke. In [12], the authors proposed a system to detect if foreground objects are smoke or not using both Wavelet Transform energy coefficients and image color properties. The proposed Bayesian approach has been extensively evaluated on public data and then results in terms of detection rate and time have been reported. In [13], a smoke detection method using optical flow computation and color-decision rule was proposed. A back-propagation neural network was then used to learn and classify the statistic of the smoke features from non-fire smoke features. Although this method can classify the disturbances which have same color with smoke, the results still depend on the selected statistical values for training. In [14], an intelligent real-time detection of smoke system was proposed. This approach employs robust smoke feature including both dynamic and static features of smoke which are motion, motion orientation and texture. For a natural and realistic aggregation of these features, a fuzzy inference system (FIS) is proposed to combine the smoke features in a fuzzy manner. The end-result is provided to a decision-making stage for final evaluation and deciding when to signal a fire alarm. The results showed that this method successfully detect smoke in normal conditions, but it cannot detect object orientation when smoke does not go up with the effect of the wind.

In this paper, a real-time smoke detection algorithm using color and movement feature is presented. Figure 1 illustrates the main steps used in the proposed method. First, background subtraction algorithm is used to detect moving regions. Next, this paper checks the color of each pixel of the moving regions and then calculates the growth rate of the moving regions. A fuzzy logic system [17, 18, 19, 20] based on human experience, knowledge and reasoning is used to process all above results. The proposed method is able to detect white, black and grey smoke. Furthermore, it can be executed on the embedded platform where hardware is limited. Thus, the proposed method can be applied directly to the surveillance camera or integrated to complete smoke detection systems such as a firefighter robot. The remaining sections of this paper is organized as follows. The proposed method is explained in detail in Section 2. Experimental results and discussion are presented in Section 3. Finally, the conclusion of this paper is presented in Section 4.

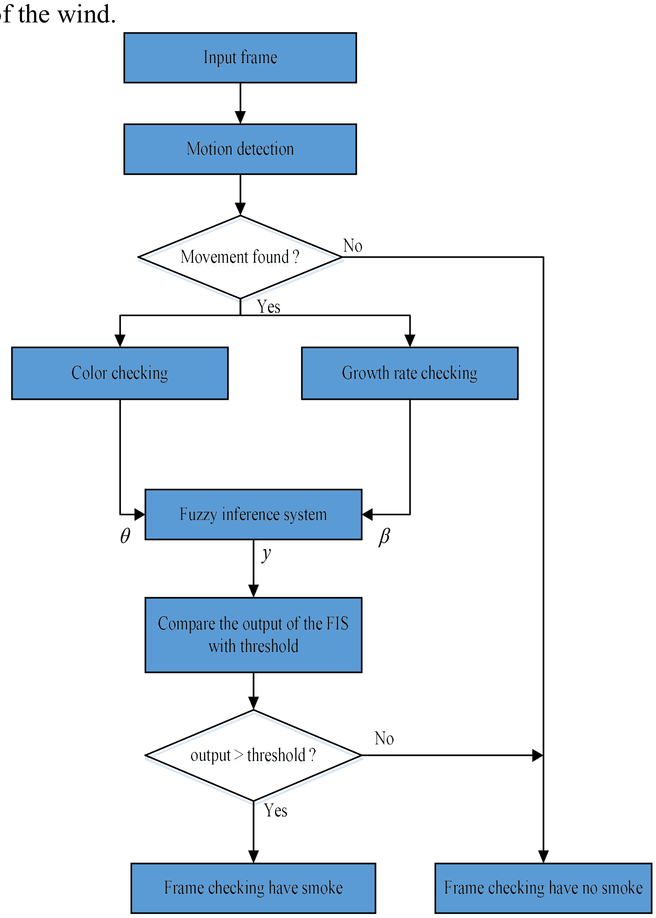

Figure 1: The Flowchart of The Proposed Algorithm

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2. PROPOSED METHOD

2.1 Motion Detection

Video is a sequence of consecutive frames. Thus, the moving region is detected by comparing consecutive frames in a video to find the difference between frames. A certain number of methods have been proposed to detect moving objects in a video such as background subtraction, statistical methods and temporal differencing. Each of them may be suitable for some specific conditions.

In this paper, background subtraction algorithm is used to detect moving objects. This algorithm is chosen because the output frames are easy for filtering noises. Furthermore, this is the fastest algorithm for detecting moving objects, so it is suitable for the purpose of running on embedded systems.

Background subtraction algorithm is a popular and effective method in solving problem of moving detection. By subtracting image at the pixel level, a new frame is compared with a background frame to give the different pixels between them. The different pixels are considered as the pixels at foreground image. Denote $B(\mathrm{x,y,t})$ is background and $I(\mathrm{x,y,t})$ is image at time t, pixel $I(\mathrm{x,y,t})$ is considered as foreground pixel if:

$$\left|I(\mathrm{x,y,t}) - B(\mathrm{x,y,t})\right| > T \tag{1}$$

where T is the threshold.
Background image $B(\mathrm{x,y,t})$ is updated using the mean background model as follow:

$$B(\mathrm{x,y,t}) = (1-\alpha)\,\mathrm{B(x,y,t-1)} + \alpha\,\mathrm{I(x,y,t)} \tag{2}$$

where α is the learning rate.

This simple approach has many disadvantages such as accuracy of frame differencing depends on object speed and frame rate. Furthermore, there is one global threshold T for all pixels in the image, so this approach may not give good results if the scene contains many slowly moving objects or the objects are moving faster than frame rate. To improve these disadvantages, Chris Stauffer and WEL Grimson [21] proposed a method for modeling the values of a particular pixel as a mixture of adaptive Gaussians. At each iteration, Gaussians are evaluated by using a simple heuristic to determine which ones are mostly likely to correspond to the background. Pixels that do not match with the "background Gaussians" are classified as foreground. Then, foreground pixels are grouped by using 2D connected component analysis.

At time t, what is known about a particular pixel, $(\mathrm{x}_0, \mathrm{y}_0)$ is its history:

$$\{X_1, ..., X_t\} = \{I(\mathrm{x}_0, \mathrm{y}_0, \mathrm{i}) : 1 \le \mathrm{i} \le \mathrm{t}\} \tag{3}$$

This history is modeled by a mixture of K Gaussian distributions:

$$P(\mathrm{X}_t) = \sum_{i=1}^{K} \omega_{i,t} * \eta(\mathrm{X}_t, \mu_{i,t}, \Sigma_{i,t}) \tag{4}$$

where η is a Gaussian probability density function as follow:

$$\eta(\mathrm{X}_t, \mu_{i,t}, \Sigma_{i,t}) = \frac{1}{(2\pi)^{D/2}\left|\Sigma\right|^{1/2}} e^{-\frac{1}{2}(\mathrm{X}_t-\mu_t)^T \Sigma^{-1}(\mathrm{X}_t-\mu_t)} \tag{5}$$

An on-line K-means approximation is used to update the Gaussians. If a new pixel value, X_{t+1} can be matched to one of the existing Gaussians (within 2.5σ), that Gaussian's $\mu_{i,t+1}$ and $\sigma^2_{i,t+1}$ are updated as follows:

$$\begin{cases} \mu_{i,t+1} = (1-\rho)\mu_{i,t} + \rho X_{t+1} \\ \sigma^2_{i,t+1} = (1-\rho)\sigma^2_{i,t} + \rho(\mathrm{X}_{t+1} - \mu_{i,t+1})^2 \end{cases} \tag{6}$$

where $\rho = \alpha\eta(\mathrm{X}_{t+1} \left| \mu_{i,t}, \sigma^2{}_{i,t}\right.)$
Prior weights of all Gaussians are adjusted as follow:

$$\omega_{i,t+1} = (1-\alpha)\omega_{i,t} + \alpha(\mathrm{M}_{i,t+1}) \tag{7}$$

where $\mathrm{M}_{i,t+1} = 1$ for the matching Gaussian and $\mathrm{M}_{i,t+1} = 0$ for all the others.

For background model estimation, at each iteration, Gaussians are evaluated by using a simple heuristic to determine which ones are mostly likely to correspond to the background. First, the Gaussians are ordered by the value of ω / σ , and then simply the first B distributions are chosen as the background model:

$$B = \mathrm{argmin}_b(\sum_{i=1}^{b} \omega_i > T) \tag{8}$$

where T is minimum portion of the image which is expected to be background.

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With this method, different thresholds are selected for each pixel. These pixel-wise thresholds are adapting by time. Objects are allowed to become part of the background without destroying the existing background model, provides fast recovery. However, this approach cannot deal with sudden or drastic lighting changes. Zoran Zivkovic [22] presented an improved algorithm for decreasing the number of parameters. By automatically choosing the number of components for each pixel in an on-line procedure, the algorithm can automatically and fully adapt to the scene. The processing time is reduced, and the segmentation is slightly improved.

2.2 Color Checking

The color of every pixel $\chi(x, y)$ in the moving regions is checked by using a color-based decision rule based on the method proposed by Yue Wang, et al. [11]. Depending on the type of material, smoke may have gray color, white color or black color. In R-G-B color space, smoke is in gray color when three color components R, G and B are almost equal. Thus, to check for the gray color of the pixel, this study subtracts the minimum value from the maximum value of the pixel in three color components, and then compare the result with a threshold T_{gray} as the following expression:

$$\left|C_{\max} - C_{\min}\right| \le T_{gray} \tag{9}$$

where
$C_{\max} = \max(R, G, B)$, $C_{\min} = \min(R, G, B)$ and T_{gray} is threshold for gray color.

For white (light-gray) color smoke, because pixel of white color have greater intensity than background, this paper checks I_{fg} and I_{bg} to find white color pixel as the following expression:

$$(I_{fg} - I_{bg}) > T_{white} \tag{10}$$

where I_{fg} and I_{bg} denote the gray value of that pixel in the background image and current frame respectively.

For black (dark gray) color smoke, because pixel of black color falls within a certain range of gray values, this paper check for the black color pixel as the following expression:

$$T_{black1} > (I_{bg} - I_{fg}) > T_{black2} \tag{11}$$

With (9), (10) and (11), this paper conclude that a pixel has color as color of smoke if it meets the following condition:

(*Condition (9)* AND *Condition (10)*) OR (*Condition (9)* AND *Condition (11)*)

This paper checks all the pixels in the moving regions, and then get the ratio between smoke color pixels and total pixels in the region. This ratio is represented as θ. This is the first input of the fuzzy inference system.

2.3 Growth Rate Calculation

There are many moving objects with fixed shape that may have the same color as color of smoke such as moving car, moving people and so on. The size of these objects does not significantly change as they are moving. Otherwise, because of the effect of wind and material, smoke grows quickly as soon as it formed. Thus, it is possible to distinguish between smoke and other moving objects by calculating the growth rate of the moving regions in a period of time. Moreover, smoke can separate into other moving regions or new moving object in each frame. Therefore, to calculate exactly growth rate of the smoke regions, it is necessary to identify all new moving regions in current frame. If there is more than one new moving object appearing on current frame, this paper first checks the color of this new moving region.

- If this region does not have color the same as color of smoke (threshold for smoke color is set to minimum in this case), it will be rejected.

- - If this region has color the same as color of smoke, this paper then calculate the distance between this region and all previous regions as the following Euclid formula:

$$Dist(c_p, c_i) = \sqrt{(x_{c_p} - x_{c_i})^2 + (y_{c_p} - y_{c_i})^2} < T \tag{12}$$

where c_p and c_i represent the current and previous moving region, T is a threshold.

- If the condition (12) is true with any previous region, this new region is separated from previous smoke region. Thus, it will be rejected.

- If the condition (12) is wrong with all previous regions, this paper takes this new region as a new smoke region and then continues to check growth rate of this region.

In digital images, the area of the smoke regions can be represented by total number of pixels in that region. The time interval can be

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expressed as the number of frames. Thus, this study uses the following equation to calculate the growth rate:

$$\beta = \frac{S_{i+k} - S_i}{(i+k) - i} \tag{13}$$

where β represents the growth rate of the region, from frame i to frame $(i+k)$ (current frame). S_i and S_{i+k} represent the total pixels in the region of frame i and frame $(i+k)$.

Because the growth rate of object between two consecutive frames is too small, it is impossible to distinguish the growth rate of smoke and non-smoke moving object. Thus, two videos of moving object are used to check for choosing the appropriate value of *k*. The first video is taken when smoke is emitting forward a white wall. Smoke is strongly affected by wind in this video, so the direction of smoke is almost horizontal. The second video is taken when a white car is running on the road. This paper chooses *k = 1, k = 2, k=3, k=4* and *k = 5* to check growth rate. Figure 2 shows results of the growth rate with the selected value of k in frame 19 (video 1) and frame 11 (video 2). Table 1 shows results of these videos corresponding to the value of k from 1 to 5 with random frame.

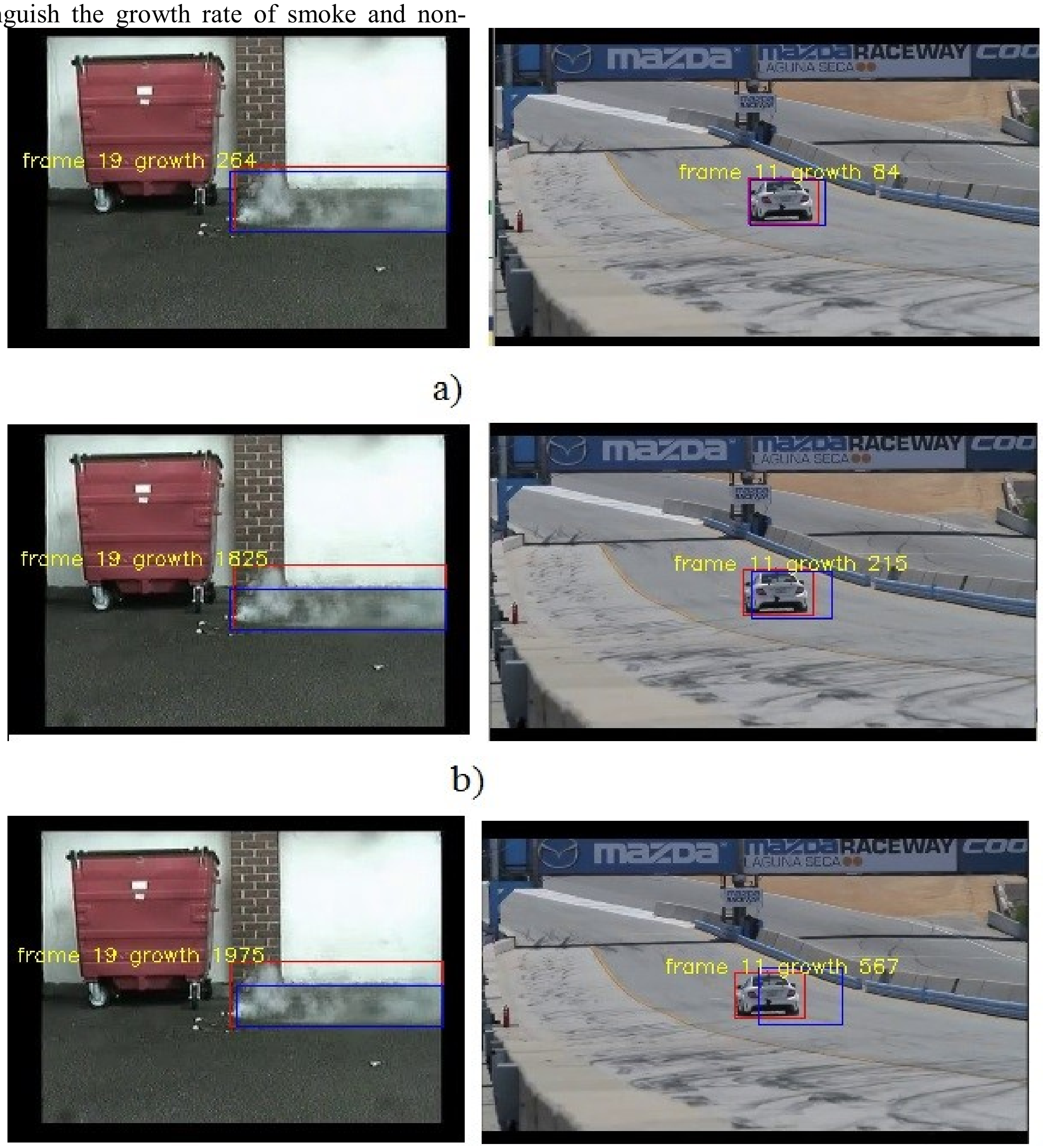

Figure 2: Growth Rate with Different Values of k, (a) k=1, (b) k=3, (c) k=5

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Table 1: Growth Rate with Different Values Of k

Growth rate β	*k* value	*k*=1	*k*=2	*k*=3	*k*=4	*k*=5
Video	video 1-frame 12	357	206	1134	1752	1504
	video 1-frame 19	264	227	1825	1828	1975
	video 1-frame 26	25	215	2449	1023	4109
	video 2-frame 9	187	294	539	467	312
	video 2-frame 11	84	28	215	322	567
	video 2-frame 14	54	135	257	341	285

As shown in Table 1, with k = 1 (two consecutive frames) and k = 2, the growth rate of moving region in two videos is quite small. With k = 3 or higher value of k, the growth rate of smoke region in video 1 significantly increases, while the growth rate of moving car in video 2 is quite stable. Furthermore, the growth rate of smoke region rapidly increases if we increase the value of k. Otherwise, increasing the value of k will lead to ignore many initial frames. this paper chooses k = 3 to calculate the growth rate β . The β is the second input of the fuzzy inference system.

2.4 Fuzzy Inference System (FIS)

A fuzzy logic system based on human experience, knowledge and reasoning is used to process previous information. Figure 3 shows the structure of proposed fuzzy inference process.

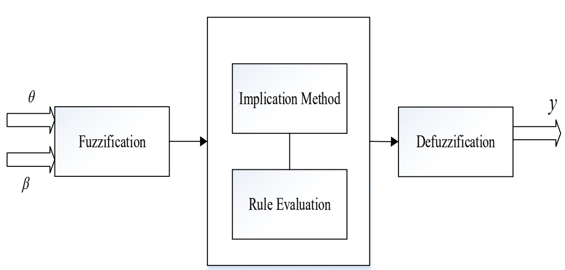
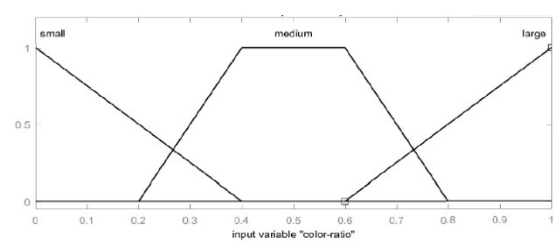


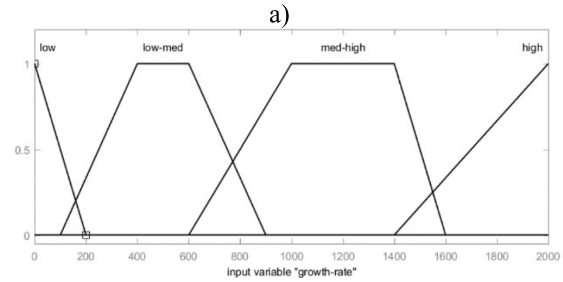
Figure 3: Fuzzy Inference Process

2.4.1 Fuzzification

The proposed fuzzy logic system takes two inputs for each moving region in frame as shown in Figure 3. The θ represents ratio between smoke color pixels and non-smoke color pixels while β represents the growth rate of moving regions. For each input, membership values are obtained in the corresponding fuzzy sets based on human experience. To achieve real-time speed on embedded system, this paper chooses member functions with triangular or trapezoidal shape. As input values are too small or too large, the current moving region will be considered as non-smoke or smoke region. Thus, triangular shape is used to represent the membership values in this case. As input values change at the middle range, the current moving region may change from smoke to non-smoke region and vice versa. Thus, trapezoid shape is used to represent the membership values. Figure 4 shows the membership functions of the inputs.



a)



b)

Figure 4: The Membership Functions of the Inputs, (a) Color ratio, (b) Growth rate

2.4.2 Rule evaluation

The second step is to take the fuzzified inputs and then apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This paper employs a Sugeno-style fuzzy rule because Sugeno method is computationally efficient. This style is appropriate to the hardware limitations of embedded systems. The most commonly used zero-

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order Sugeno fuzzy model applies fuzzy rules in the following form:

IF *x is A* AND *y is B* THEN *z is k*

where *k* is a constant.

In this case, the output of each fuzzy rule is a constant value. All consequent membership functions are represented by singleton spikes. Figure 5 shows the membership functions of the outputs y.

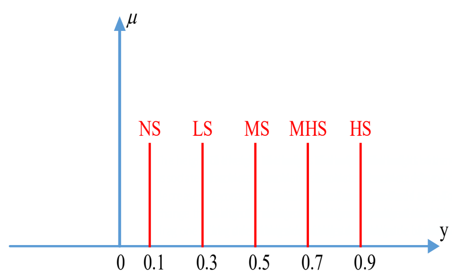

Figure 5: Membership Functions of the Outputs y, NS (no smoke), LS (low smoke), MS (medium smoke), MHS (medium-high smoke), HS (high smoke)

A total of 12 rules (R_1 - R_{12}) are contemplated in the proposed FIS as listed in *Table 2.*

2.4.3 Defuzzification

Defuzzification is the last step in the fuzzy inference process. Fuzziness helps to evaluate the rules, but the final output of a fuzzy system must be a crisp number. The input for the defuzzification process is the aggregate output fuzzy set, while the output is a single number.

For Sugeno-style defuzzification, the final output of a fuzzy system is calculated by using the center of mass defuzzification method as the equation (14).

In (14), W_i represents the rule firing strength. If the conjunction operator (AND) is used in the antecedents of the rules. Then the rule firing strength W_i is calculated as follow:

$$\mathrm{W}_i = \min\left[\varphi_\theta, \varphi_\beta\right] \quad (15)$$

The final output of defuzzification for every moving region is a crisp value between 0.1 to 0.9 that reflect the potential for being smoke in this region. This paper then compares this output value with a threshold value. If the output value is greater than threshold value, the current region will be concluded as smoke region. Otherwise, it will be discarded.

3. EXPERIMENTAL RESULTS

C++ language with the support of the open source library OPENCV is used to implement the proposed method. This study then executes the method on the BeagleBone Black. This embedded board includes 1GHz ARM Cortex-A8 processor, 512MB of DDR3 RAM and a Linux operating system. Video inputs are captured from an external camera and then scale to 320 x 240 of resolution for faster processing speed.

Four videos are used to test the effectiveness of the proposed method. These videos are recorded in different environments with a dedicated camera or a surveillance camera. The first video is taken in a garden with a small fire. The second video is taken on the road where a white car is running. The third video is taken at a place where smoke is emitting toward white wall. The fourth video is taken in a tunnel where a man is walking near a light. There is no smoke with the second video and the fourth video. Because all the videos are collected during daytime environment, this paper chooses output threshold of the fuzzy at 0.5. If output value of the fuzzy is greater than 0.5, the moving regions are concluded as smoke region. Furthermore, because this study starts to calculate the growth rate from the fourth frame, the first three frames in each video will be ignored. Figure 6 shows the random frame of each video.

To evaluate the accuracy of the proposed method, this paper follows the criteria using in classification: correct result and wrong result.

Correct result: when smoke is correctly detected as smoke and no-smoke is correctly identified as no smoke in each frame.

Wrong result: when smoke is incorrectly detected as there is no smoke and no-smoke is incorrectly detected as there is smoke in each frame.

The accuracy of each video is calculated as the ratio between the number of correct results and the total of frames. Figure 7 shows the results of random frame in each video. Table 3 shows the final results of all videos. As shown from Table 3, the proposed method is very effective for detecting smoke. Video 1 shows smoke in a garden where the shape of smoke changes quickly with the effect of the wind. Therefore, the result becomes wrong when smoke disappears, or the shape of smoke becomes fixed. Video 2 shows a white car running on a road. The car has the same color as color of smoke. Because the shape of the car is fixed, the growth rate is always low. Thus, this paper achieves the accuracy at 100% in this case. Video 3 shows smoke emitting forward a white wall. With the effect of the wind and color of the white wall, smoke regions sometimes like natural objects. Thus, the accuracy decreases in this case. Video 4 shows moving object with shape and color different from shape and color of smoke, so this paper achieves the accuracy nearly 100% in this case.

$$y = \frac{W_1.NS + W_2.NS + W_3.LS + W_4.MS + W_5.LS + W_6.MS + W_7.MS + W_8.MHS + W_9.MS + W_{10}.MHS + W_{11}.HS + W_{12}.HS}{\sum_{i=1}^{12} W_i} \quad (14)$$

Table 2: Rule Evaluation Based on Sugeno FIS Model

y		β			
		low	low-med	med-high	high
θ	small	$R_1 : NS$	$R_2 : NS$	$R_3 : LS$	$R_4 : MS$
	medium	$R_5 : LS$	$R_6 : MS$	$R_7 : MS$	$R_8 : MHS$
	large	$R_9 : MS$	$R_{10} : MHS$	$R_{11} : HS$	$R_{12} : HS$

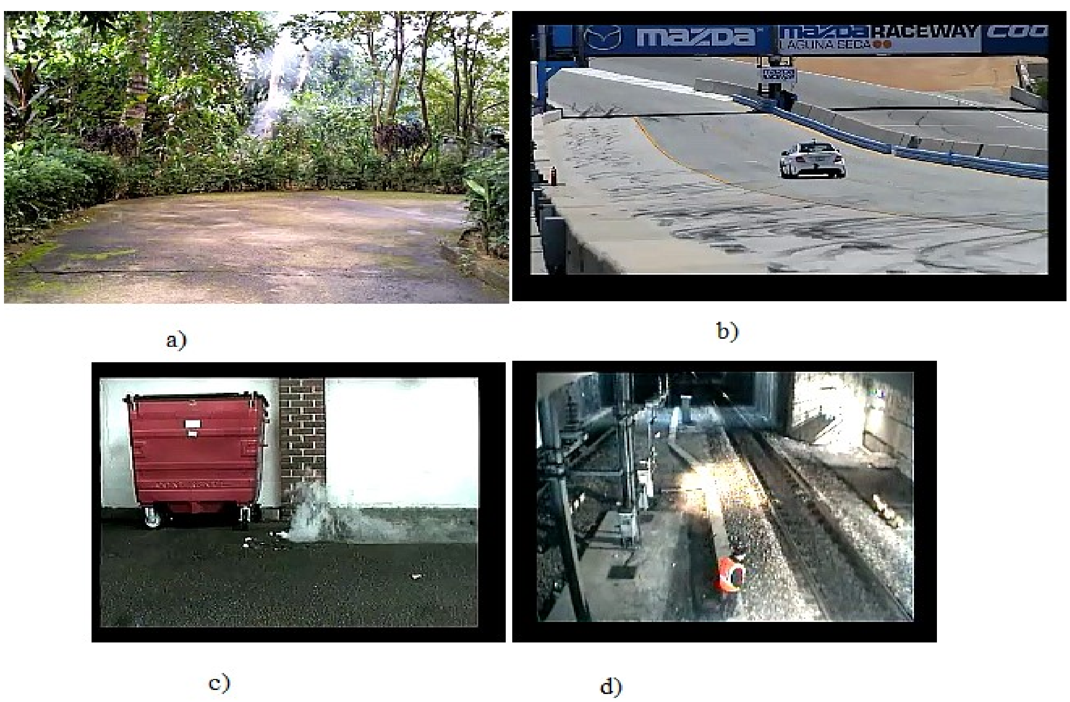

Figure 6: Random Frame of Each Video, (a) video 1, (b) video 2, (c) video 3, (d) video 4

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Figure 7: Results at Random Frame of Each Video, (a) video 1, (b) video 2, (c) video 3, (d) video 4

Table 3: Experimental Results of All Videos

Video	Number of frame	Number of smoke frame	Processing speed	Result of the proposed method		
				Correct result	Wrong result	Accuracy
Video 1	247	247	13 FPS- 16 FPS	239	8	97%
Video 2	58	0	19 FPS- 21 FPS	57	0	100%
Video 3	282	282	15 FPS- 18 FPS	260	22	92%
Video 4	171	0	15 FPS- 18 FPS	169	2	99%

4. CONCLUSION

Vision-based smoke detection has many advantages over the traditional based smoke detectors. Vision-based smoke detection can provide early detection of fire with information on the location and intensity of smoke. This paper proposes a smoke detection method using a fuzzy inference system based on motion and color of the smoke. The proposed method uses the combination of motion, color and growth rate. The proposed method is able to detect white, black and gray smoke. This paper uses embedded system to implement the method to reduce costs and create maneuverability so that the method can be integrated into the surveillance camera. Experiment results on different videos in different environments have also demonstrated that the proposed system can detect smoke in an open environment such as smoke in a forest, tunnel, highway and so on. Furthermore, the output of the fuzzy system is compared with a threshold value to get final results, so it is possible to change this threshold value to suit different environments such as low light and strong wind. However, because the proposed smoke detection system is based on collected images, it cannot detect smoke if smoke is masked by other objects. In addition, the proposed method shows

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limited performance in difficult conditions such as illumination changes due to moving cloud, video captured by moving camera and so on. Thus, future works will focus on improving the algorithm for detecting smoke in difficult environments.

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