A Thermal-Based Fuel-Prediction Method for Intelligent Fire Extinguishers in an Indoor Environment

Teerapong Suejantra[1] and Kosin Chamnongthai[2]

ABSTRACT: Classification of fuel in the early stage of fire is important to choose the appropriate type of extinguisher for extinguishing fire. This paper proposes a method of fuel prediction based on heat information for intelligent fire extinguishers in an indoor environment. Fire flame in the early stage is first detected based on patterns of differences between consecutive thermal image frames in which temperature rises rapidly and reveals a sharp positive slope. Then candidate flame boundaries are detected in the thermal image frames during the early stage, and boundary matching is performed among the frames. These matched boundaries are classified as fire flame and fuel class based on LSTM (Long short-term memory) for extinguisher selection. Experiments were performed with 300 samples for classification into four classes of fuel, and the results based on 9:1 training and testing ratio showed 92.142% accuracy.

Keywords: Fire-based Fuel Classification, Fuel Classification, Thermal Image, Fire Monitoring, Fire Detection, Deep Learning

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1. INTRODUCTION

Fire has been an incident of man-made disaster which gives a huge amount of damage to humans throughout recorded time. According to the statistical data of the national fire protection association, USA, in 2018 [1], fire has occurred more than 1.3 million times and Killed more than 3.6 thousand people a year. Major causes of fire are cooking (49%), heating equipment (14%), electrical distribution and lighting equipment (10%), intentional 8%, and smoking materials (5%) [2] in years 2013-2017. These fires which emerged by different reasons and conditions might be ignited by different fuels and need different fire extinguishers [3]. According to a recent survey [4], the wrong type of fire extinguisher has been used in fire in many cases, and more than 38 per cent of workers used the wrong type of fire extinguisher on an electrical fire. These wrong types of extinguishers may not only be ineffective on the fire itself, but may also cause excessive damage to equipment. Automatic system of fire detection is urgently required, and simultaneously fuels muse be predicted for appropriate extinguisher selection.

To develop an automatic system of fire detection and fuel prediction, some research work has been done and can be divided into two groups, which are learning-based and decision-based approaches. The methods in the group of learning-based approaches [5-14] performed with excellent results of fire recognition based on existing machine learning tools such as artificial neural networks, convolutional neural networks (CNN), and so on. However, the methods require a training process in which training data must be selected well and training processes need to be performed covering all conditions.

On the other hand, decision-based methods [15-19] basically do not require a complicated training process and are workable for fire detection. In the case of fire detection, safety from fire is the highest preference for users. The fire detection system should detect fire correctly in the early state in real time even with positive errors.

The research work in both mentioned groups has shown successes in performing fire detection targeting the final goal of fire flame detection in early stages which is accepted as important issue. However, fuel prediction is important for extinguisher selection, and is also another crucial issue for fire protection and prevention. The authors of this paper therefore tried to

[1,2]The authors are with Department of Electronics and Telecommunication Engineering, King Mongkut's University of Technology Thonburi, Bangkok 10140, Thailand., E-mail: teerapong.sj@mail.kmutt.ac.th and kosin.cha@kmutt.ac.th

find a method of flame detection and fuel prediction in the early stage for automatic fire extinction in an indoor environment. Since sometimes fire occurred in a dark indoor environment without light, a heat sensor, which can sense heat information in both light and dark, is considered to be used instead of a digital camera for fire detection. Patterns of heat increment and change are utilized to detect fire, and features during heat changes are classified for fire fuel.

The paper is constructed as follows. Analysis of fuelbased thermal image of fire flame in early stages is reported in Section 2. The scenario of a future fire extinguisher is introduced in Section 3. An overview of the proposed fire detection and fuel prediction is described in Section 4. Section 5 demonstrates the experimental results using video datasets of fire. The discussion of the experimental results is given in 6. Finally, the conclusion is presented in Section 7.

2. ANALYSIS OF FUEL-BASED THERMAL IMAGE OF FIRE FLAME IN EARLY STAGES

Our research work initially aims to solve a problem of detecting fire in early stage, especially when fire flame just emerges in the indoor environment. In fact, vision sensors nowadays are regarded as powerful and effective tool for sensing and monitoring things based on brightness information, but it may not work well in a dark environment. On the other hand, thermal sensors have recently become attractive tools which sense heat information in terms of thermal images. The thermal sensor can be applied for fire flame detection and fuel classification based on analysis results.

2.1 Fire Flame In A Thermal Image

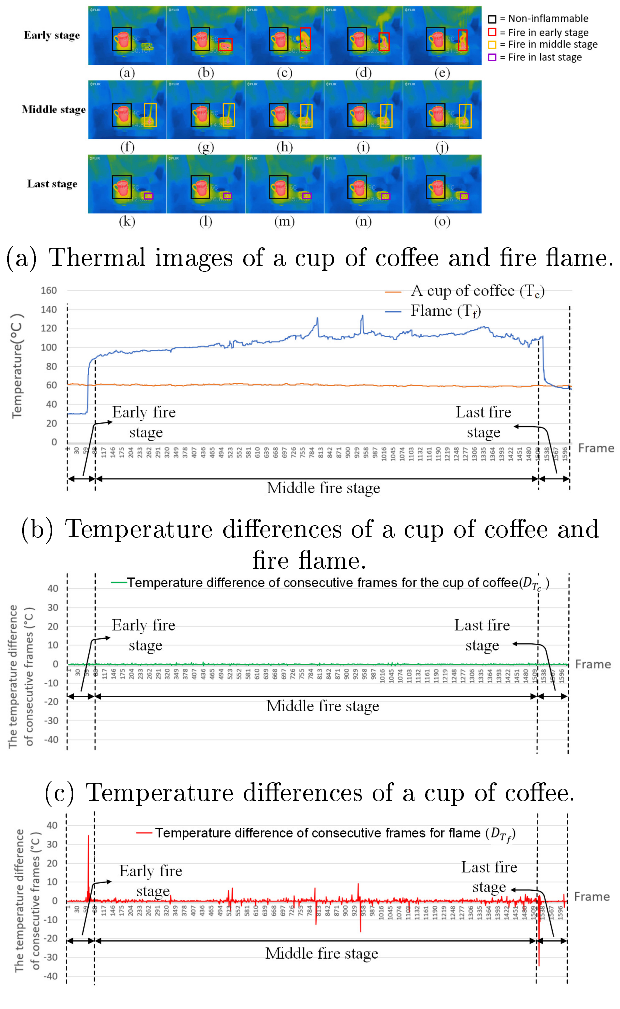
A thermal sensor is assumed to be installed in a position in an indoor environment in which the sensor can see all views in the space, and a video consisting of thermal image frames is observed. If we perform sampling on a point on a boundary of a cup of hot coffee and another point on a fire flame in the same thermal video frame (δ), temperature of those points can be shown in Fig. 1 (a). In this case, the temperature of the cup of coffee (T_c) is as warm as around 60 degree Celsius, and the change of temperature tends to maintain or even decrease the room temperature. Simultaneously, a fire flame emerges. The temperature (T_f) increases in the early stage, maintains in the middle stage, and quickly cools down in the last stage. If we find temperature differences (D) between object boundaries of consecutive frames, temperature differences of a cup of hot coffee (D_{T_c}) and fire flame (D_{T_f}) can be plotted, as shown in Fig. 1 (c) and (d), respectively.

As observed, the graphs of temperature differences between consecutive frames of coffee, as shown in Fig. 1 (c) have no outstanding spike, while the ones of the flame reveal outstanding positive and negative peaks during the early and last stages, respectively, as shown in Fig. 1 (d). Ideally, the case of fire flame without any noise can be described by equation (1).

$$\frac{\partial D_{T_f}}{\partial t} = \left\{ \begin{array}{c} +; early\ fire\ stage \\ \cong 0; middle\ fire\ stage \\ -; last\ fire\ stage \end{array} \right\} \quad (1)$$

In another case of hot objects such as a cup of coffee, although the initial temperature is much higher than the room temperature, it may gradually decrease to be the same as the room temperature. This can be simply expressed in differentiation as shown in equation (2).

$$\frac{\partial D_{T_f}}{\partial t} \approx 0 \quad (2)$$



(a) Thermal images of a cup of coffee and fire flame.

(b) Temperature differences of a cup of coffee and fire flame.

(c) Temperature differences of a cup of coffee.

(d) Temperature differences of fire flames.

Fig.1: *Temperature changes between fire flame and others.*

Theoretically, differentiation of the objects' results are nearly zero except in the cases of the early and last fire stages. In fact, noise exists, and it will hamper peak detection. To detect peaks representing the early fire stage, existing noise should be suppressed. A way to simply suppress noise is to initially train an appropriate threshold value (Th) on some fire video samples. The threshold value is obtained and used to delete noises in testing as shown in equation (3) and (4).

$$Th = \frac{A}{M} \sum_{i=1}^{M} |\delta_i - \delta_{i+1}| \tag{3}$$

$$\delta_i' = \begin{cases} 0\ ,\ \delta_i\ <\ Th \\ \delta_i\ ,\ \delta_i\ \geq\ Th \end{cases} \tag{4}$$

A is a parameter for segmentation and $i = 1, \ldots, M$. When noise is suppressed by the mentioned threshold value, peaks are detected early, and last fire stages should outstandingly appear. Then, the positive and negative peaks can be detected as early and last fire stages, respectively.

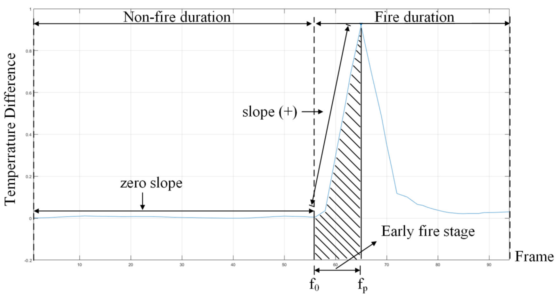


Fig.2: *Video frames in early stage.*

In applications for extinguishing fire in an indoor environment, fire must be detected as soon as possible during the early stage to safely extinguish the fire in time. Based on the phenomenon mentioned above, it is observed that the slope of temperature difference would be none during normal or non-fire duration, and become positive during the early fire stage, as shown by the shaded area in Fig. 2. The thermal video frames during the period should be then recognized as fire flame.

In observing the phenomenon of flames in the early stage, it differences can be observed among flames ignited by different fuels, as shown in Fig. 3. Differences among five fuel classes [4] can be seen as patterns of flame growing. Although a pattern of flame growing among different fuels in the same class can be superficially recognized, they are differentiated at least in the number of frames. In practice, it is needed to recognize the fuel class level so that a state transition concept can be usefully applied to solve the fuel class recognition.

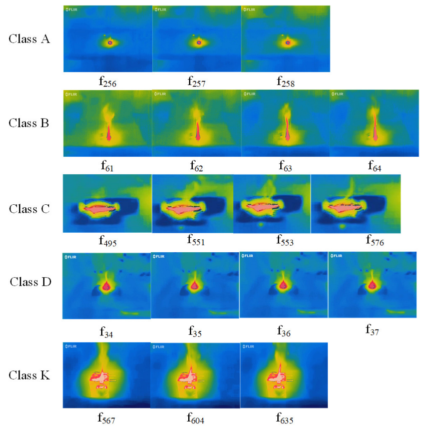
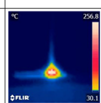
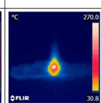
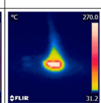
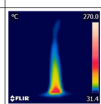
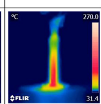
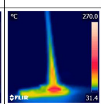
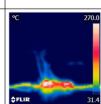
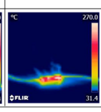
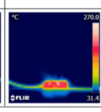
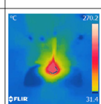
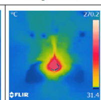
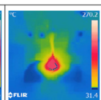
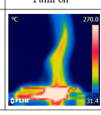
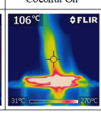
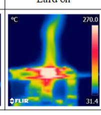


Fig.3: *Flame growing among fuel classes.*

2.2 Fire Flame Features of Fuel Types

Nowadays, The NFPA (National Fire Protection Association) has defined the fire classification into five classes based on fuels with a standard [3]. In the standard, A, B, C, D, and K classes, as shown in Table 1, are classified according to fuels such as wood, cloth, and paper for A, liquid, oil, and alcohol for B, electrical equipment for C, magnesium, titanium, zirconium, sodium, and lithium for D, and combustible cooking media for K classes. These fuel classes require specific types of extinguishers, as shown in the last column of Table 1. This means it is necessary to know fuel for extinguishing fire flame by the appropriate extinguishers. Otherwise, fire is not extinguished, and the extinguishers may damage the objects.

Table 1: *Fuel classes.*

Fuel	Paper	Plastic	Wood	Types of Fire Extinguishers
ClassA				1. Stored pressure water 2. Aqueous film forming foam 3. Film-forming fluoroprotein 4. Halon 1211 5. Halocarbon 6. Dry Chemical
Fuel	Alcohol	Gasoline	Diesel	Types of Fire Extinguishers
ClassB				1. Carbon Dioxide (CO_2) 2. Aqueous film forming foam 3. Film-forming fluoroprotein 4. Halon 1211 5. Halon 1301 6. Halocarbon 7. Dry Chemical
Fuel	VFF	AWG	VSF	Types of Fire Extinguishers
ClassC				1. Carbon Dioxide (CO_2) 2. Halon 1211 3. Halon 1301 4. Halocarbon 5. Dry Chemical
Fuel		Magnesium		Types of Fire Extinguishers
ClassD				1. Dry Powder
Fuel	Palm oil	Coconut Oil	Lard oil	Types of Fire Extinguishers
ClassK				1. Wet Chemical

To find different features in the fire flame in each class, fire flames were ignited in a lab, as shown in columns 2-4 of Table1. Fire flame feature of each class can be simply extracted in different geometric shapes, as shown in column 5.

Analytically, there exist few features of fire flame in the mentioned five types, which are in classes A-D, and K. Some features such as color correlogram, contour signature, and shape can be categorized, as shown in Fig. 4. These features are then considered as static patterns of fire flames in fuel types.

To conclude what are explained in subsections 2.1 and 2.2, these differences among fuel types in a class and among classes can be seen as dynamic or transition patterns in a state transition diagram, as shown in Fig. 5. The situation normally stays at neutral state. When fire is ignited, the state starts to transit to early fire stage, gradually moves to middle fire stage and last fire state, respectively. If fire flame is extinguished in time, the situation returns to the neutral state. This means geometric shape of fire flame, perceptron images of fire flame, and changes of temperature layers can be regarded as features to classify fire fuel class, and our paper tried to employ and study these three features for fuel classification based on a state transition concept.

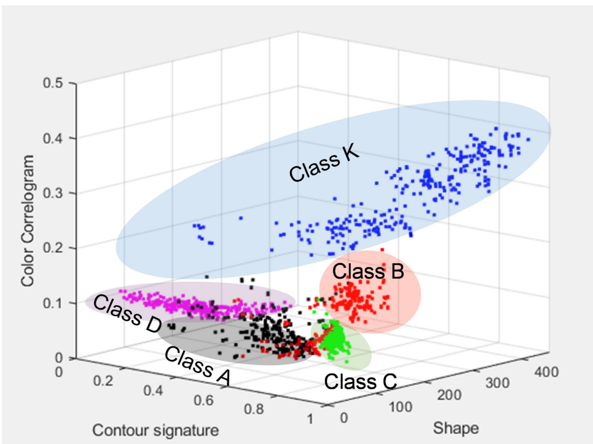


Fig.4: *Features of fuel.*

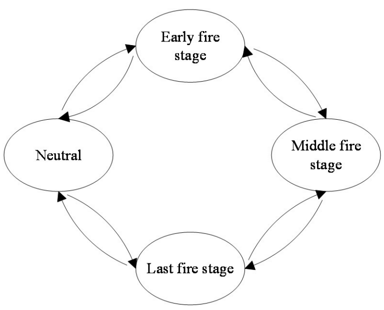


Fig.5: *State transition of fire flame.*

3. SCINARIO OF INTELLIGENT FUEL-BASED EXTINGUISHING SYSTEM AND OVERVIEW OF PROPOSED METHOD OF FIRE-BASED FUEL PREDICTION

A Scenario of proposed intelligent fuel-based extinguishing system is introduced in subsection 3.1, and an overview of our proposed method of fire-based fuel prediction is discussed in subsection 3.2.

3.1 Scenario of Fuel-based Intelligent Fire Extinguishing System

In an indoor environment, suppose a thermal sensor is installed with a system box containing a processor and a video memory on the ceiling of the room, as shown in Fig. 6. The sensor always senses heat in the room in terms of consecutive video, and stores video data in the video memory for processing. When the system detects fire flame, especially in the early stage, the detected boundaries of fire boundary candidates will be analyzed for features such as fire flame shape, ratio of heat area, and so on, and these features of fire flame in the boundaries are classified for fuel class. Then, the extinguishing system selects the most appropriate extinguisher substance according to the fuel class, and spouts it to extinguish fire by pinpointing exactly to the fire flame boundaries in the early fire stage.

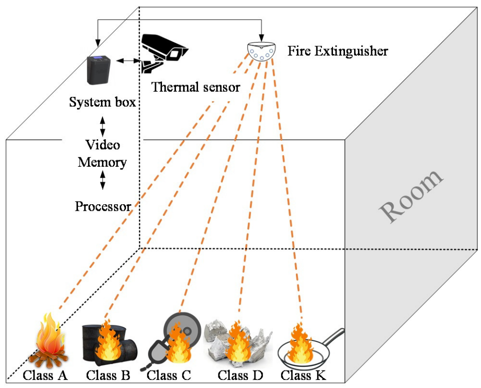


Fig.6: *A scenario of intelligent fire extinguisher.*

3.2 Overview Proposed Method of Fire-based Fuel Prediction

As shown in Fig. 7, the proposed fire-based fuel prediction method starts from video input processing. The input video is checked for fire candidates in an infinite loop until a fire candidate is detected. When it is detected, the video frames are preprocessed, detecting boundaries of fire flame candidates, and fire flame is confirmed at the boundary segmentation and fire detection processes, respectively. Unless there is fire flame, the system goes back to input another thermal video as normal. If fire flame is confirmed in the video, detected fire flame fuel is selected by feature extraction and classification in the fuel classification process. The predicted fuel information is used to select an appropriate extinguisher substance in the extinguisher selection process.

4. PROPOSED FIRE-BASED FUEL PREDICTION

To realize fuel prediction based on the heat information for the mentioned scenario, our paper proposes a procedure, as shown by the flowchart in Fig. 7. A stream of video data representing heat information in a room detects candidate frames of fire flame in the first step. If there is no change in a couple of consecutive frames, which is not regarded suspicious as fire candidate, the system continues to input the next video stream. If it is suspicious as the frames of fire flame candidate, the system starts to find candidate boundaries, perform boundary matching between consecutive frames, and predict fuel in the boundaries. The details are described next.

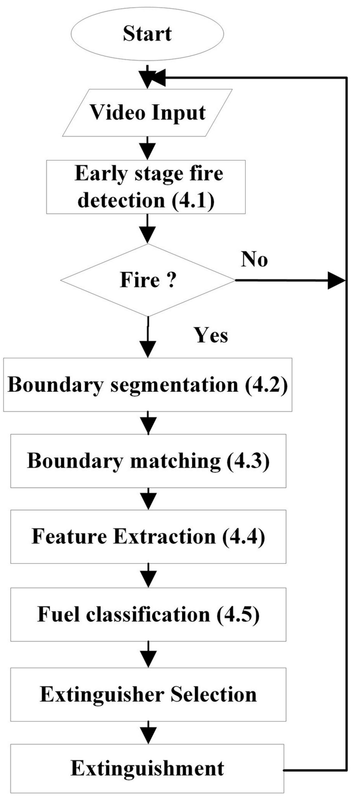


Fig. 7: *Flowchart of overview proposed method of thermal-based fuel prediction.*

4.1 Early-Stage Fire Detection

Normally, a thermal camera or heat sensor, which is assumed to be installed at the ceiling of a room, captures video data representing temperature as heat information, as shown by colors in Fig. 8 (a). Both fire flame and a cup of hot coffee appear in the room, and the sensor catches the temperature and displays color images. If differentiation is performed between consecutive video frames (f_i), a peak representing the border between the non-fire and fire candidates is simply detected, as shown in Fig. 8 (b) with some small spikes which are considered as noise. It is observed in Fig. 8 (a) that nothing is detected during video frames at $t_1 - t_3$ which is normal state. When a cup of hot coffee is laid in the room during video frames during $t_{14} - t_{18}$, although the hot coffee is in high temperature, nothing is detected due to no obvious difference between consecutive video frames. However, an outstanding peak is found during video frames during $t_{20} - t_{21}$ because fire is ignited. There is no difference in the middle fire state during video frames during $t_{22} - t_{27}$, and obvious peaks appear again at video frames during $t_{28} - t_{31}$ which is the last fire state. Therefore, this paper proposes to first set up a thresholding value (Th_1) for suppressing noise, and then detect the first peak in the differentiation signal period as the starting video frame of fire flame candidate to extinguish fire flame at the early fire state. The thresholding value is set up according to equations (3) and (4).

To implement a function of fire detection, the function can be developed based on the observation results in Fig. 8 (b) in which peaks in differences of consecutive frames are suspicious as fire-flame candidate frames. Therefore, the algorithm, as shown in Algorithm 4, should search for the differences of consecutive frames, and try to find the difference of a couple of consecutive frames that is over the threshold value for noise suppression and where the slope is positive. This situation might be continued until it reaches the peak where the slope turns to negative. This means the system finds that fire occurs, and it immediately calls a subroutine to find flame boundaries and fuels.

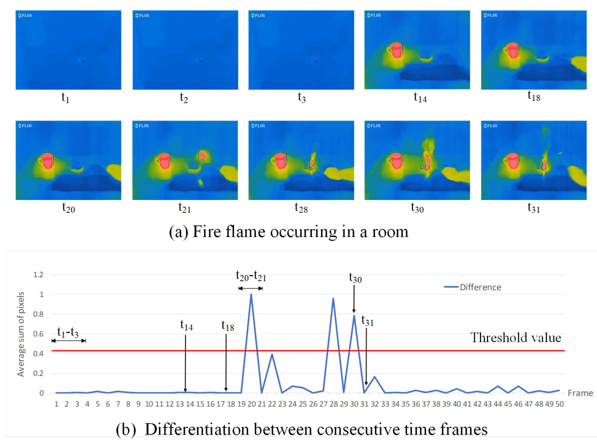


Fig. 8: *Differentiation between consecutive frames for fire frame detection.*

Algorithm 1 Selection of fire candidate frames

START
SET n = frames position, N = maximum number of frames, VF = video frames, Th_1 = thresholding, FB = frames after binarization, $DF1$ = frame difference, NR = frames after noise reduction, PF = peak frame number
SP = summation of pixel
REPEAT //Video input and Binarization
  COMPUTE video frames of image color channels RGB from a thermal camera as VF
  COMPUTE binarization frames VF with Th_1 as FB
UNTIL frames position = N
REPEAT //Frame difference
  COMPUTE differentiation value of FB_n and FB_{n+1} as $DF1$.
UNTIL frames position = N-1
REPEAT //Noise reduction
  COMPUTE remove noise $DF1_{n+1}$ with moving average among consecutive frames as NR.
UNTIL frames position = N
REPEAT // Finding peak frames which are regarded as fire candidate frames.
  COMPUTE summation of pixel NR_{n+1} as SP_n
    IF $SP_n \neq 0$ **THEN**
      Time count = Time count +1
      slope = $SP_{n+1} - SP_n$
      IF slope < 0 **OR** Time count = 7 **THEN**
        get FC_n
      END IF
    END IF
UNTIL Time count =7 **OR** slope >0
END

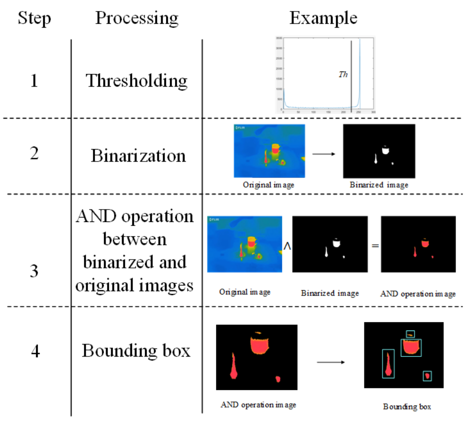


Fig. 9: *Steps in boundary segmentation.*

4.2 Fire Boundary Segmentation

At the timing that fire is suspiciously detected as mentioned earlier, a threshold value is first determined in a histogram in an original video frame, as shown in the first row of Fig. 9, Then the threshold value is used to binarize the original video frame into a binary one which reveals boundaries, as shown in the 2nd row. Fire-flame candidate boundaries are determined by an AND operation between the original and binary video frames, as shown in the 3rd row in Fig. 9. Finally, boundary boxes of the candidate boundaries are drawn by the most upper, lower, left, and right lines, as shown in the last row. This can be implemented with Algorithm 2.

Algorithm 2 Fire boundary segmentation

START
SET n = frames position, N = maximum number of frames FC = candidate frames, GL= gray level, Ht = Histogram, Th = threshold value, Mx_G = maximum gray level, BV = binary image, SG = segmented image, BB = Bounding boxes, Th = 0
REPEAT // Threshold value determination
  COMPUTE video candidate frames of image color channels RGB from algorithm 1 as FC
  COMPUTE convert RGB FC with grayscale as GL
  COMPUTE histogram GL as Ht
  COMPUTE smoothing histogram with Mx_G as Ht
UNTIL frames position = N
REPEAT // Thresholding to find a value to segment foreground image
  COMPUTE binarization FC (row, column) as BV (row, column)
    IF FC (row, column) ≥ Th **THEN**
      BV (row, column) = 0
    Else
      BV (row, column) = Mx_G
    END IF
UNTIL frames position = N
REPEAT // AND operation for boundary segmentation
  RETURN FC with AND operation BV as SG.
UNTIL frames position = N
REPEAT // Create Bounding boxes
  // regionprops [20]
  COMPUTE regionprops **THEN**
  get BB (coordinate of the top-left corner, horizontal width)
UNTIL frames position = N
END

4.3 Boundary Matching

When a frame of suspicious fire is detected as mentioned in subsection 4.1, the fire monitoring system immediately considers it as an emergency and switches itself into the fire detection, fuel prediction, and extinguishing modes. The system starts to segment possible boundaries in several video frames surrounding the detected suspicious fire frame, as mentioned in subsection 4.2. The number of video frames selected for the classification process should be determined by training on some samples in an appropriate number of video frames in advance, and this paper utilized seven consecutive video frames counting from the fire detected frame. Those selected video frames are supposed to be detecting a bounding box surrounding candidate boundaries (e.g., A1- 4, and B1-4), as shown in the first row in Fig. 10. To perform matching among bounding boxes in those consecutive video frames, existing point-matching tools such as SURF, SIFT, and so on are possibly considered to apply on bounding box contours between consecutive video frames, and the most matched bounding boxes should be selected as the same boundaries, as shown by linked lines in the bottom row. The series of the same boundaries are then fed to the next processes of feature extraction and classification, respectively. Based on the mentioned ideas, the process of boundary matching can be implemented by Algorithm 3.

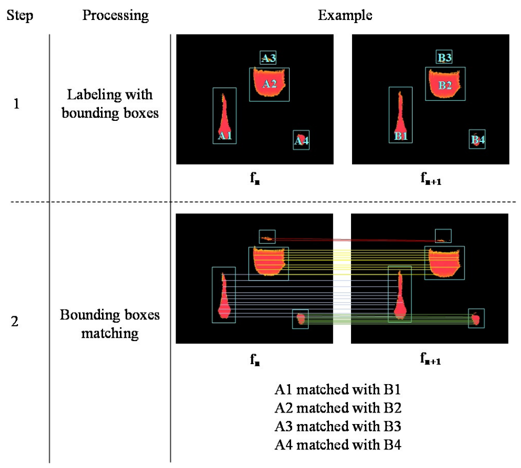


Fig.10: *Steps and examples in boundary matching.*

Algorithm 3 boundary matching of fire candidate frames

```
START
SET n = frames position, N = maximum number of frames
    BB = Bounding boxes, KP = Key point, A = label,
    B = label, FV = features value, MF = match features
REPEAT // Labeling with bounding boxes
    COMPUTE labeling all of boxes in FC_n as A_n
    COMPUTE labeling all of boxes in FC_{n+1} as B_n
UNTIL frames position = N
REPEAT // Key point from surf
    //SURF, extract features, and match feature [21]
    COMPUTE SURF features THEN
            get KP(A_n) and KP (B_n)
    COMPUTE extract features THEN
            get FV (KP(A_n)) and FV (KP (B_n))
    COMPUTE match features THEN
            get Retrieve the locations of matched
            points as MF.
UNTIL frames position = N
REPEAT // Bounding boxes matching
    COMPUTE matched points in bounding boxes with
            compare between A_n and B_n
UNTIL frames position = N
END
```

4.4 Feature Extraction

As explained in subsection 2.2 of the previous section, and shown in Fig. 4, some features such as color correlogram [22], contour signature [23], shape [24], and so on should be analyzed and confirmed as features for classification in advance. In case of selection of those features mentioned in Fig. 4, a segmented thermal image, as shown in Fig. 11, is extracted into contour signature, color correlogram, and shape, and those vales will be then fed to a classifier. A sequence of processes in feature extraction are depicted in Algorithm 4.

Algorithm 4 features extraction of fire candidate boundaries.

```
START
SET n = frames position, N = maximum number of frames
    CB = fire candidate boundaries, CL= color correlogram
    feature, CS = contour signature feature,
    S = shape feature, F = feature one dimension.

REPEAT
    COMPUTE contour signature feature in CB_n as CS_n
    COMPUTE color correlogram feature in CB_n as CL_n
    COMPUTE shape feature in CB_n as S_n
    COMPUTE normalization CS_n ,CL_n and CB_n to
            the range of 0 to 1
    COMPUTE arrangement of CS_n ,CL_n ,CB_n to be
            one dimention as F_n
    UNTIL frames position = N
END
```

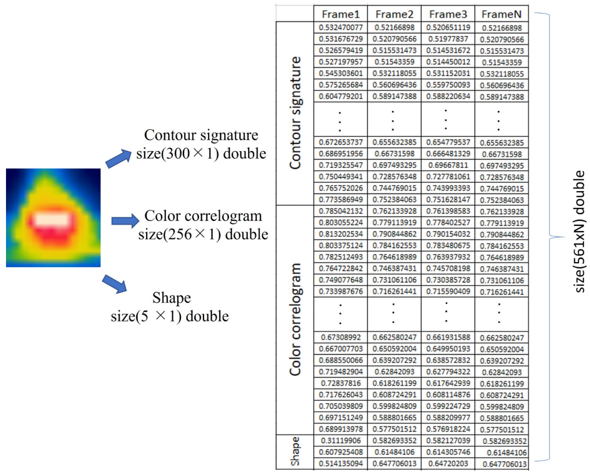


Fig.11: *Example of feature extraction in the coarse level.*

4.5 Feature Extraction

When a fire flame is detected in a boundary in the early stage, the fire flame boundary urgently must be classified to find the fuel class to select an appropriate extinguisher for extinguishment. As observed, with fire flames in different classes, features for fuel class classification should be a thermal image of fire flame, color ratio, and contours of fire flame in all layers. Since these features dynamically change all the time, the suitable classifier should be a time-independent state-transition based one. LSTM (Long short-term memory) [25] is currently regarded as an appropriate classifier in this case, as shown in Fig. 12. The network structure is basically comprised of input, hidden, and output layers, and a number of data modules are required in the vertical and horizontal directions, respectively. The LSTM is set up with parameters for structure, as shown by a sample in Table 2. In this paper, features of fire flame for fuel class classification, which are contour signature, color correlogram, and shapes including circle, rectangle, and ellipse, are serially input into the input layer. Some samples are used to train in advance, and other samples are classified for fuel classes in the testing state.

Parameter setting should be performed in advance in a training stage. We recommended performing a pretest on some samples in possible parameters [26]. In the input layer, batch size, input size per series, input feature, and learning rate, as shown in Table 2, are trained by a number of 2^n within the capability of GPU memory, total number of input data of all features, input data dimension, and appropriate rate for gradient descent taking appropriate time without overshoot [27], respectively. In the hidden layer, a hidden node is recommended as two thirds of input size per series, and the activation function can be appropriately selected from existing ones such as softmax, relu, sigmoid, tanh, and so on. Finally, output class is determined by the number of classes, which are A, B, C, D, K, and non-class in this paper.

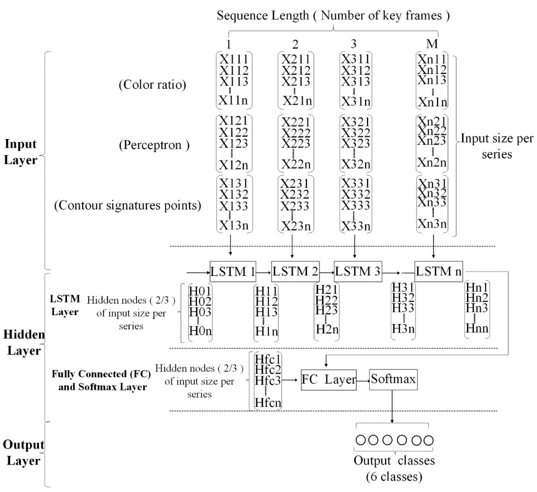


Fig. 12: *LSTM structure.*

Table 2: *Classification specification.*

Layer	Parameter	Value
Input	Batch size	8
	Input size per series	561
	Input feature	1 dimension
	Learning rate	0.0001
Hidden layer	LSTM hidden layer	
	Hidden node	374
	Activation function	SoftMax
Output layer	LSTM model	
	Output class	6

5. EXPERIMENTS AND RESULTS

To evaluate the performance of proposed method, several indoor environments for experiments and experiment specification were established, as shown in Fig. 13 and Table 3, respectively. In experiments, four types of fuel in each class were selected as follows. As materials for experiments, alcohol, gasoline, and diesel; flexible wire and cable (VFF), American wire gauge (AWG), and insulated flexible conductor (VSF); and palm oil coconut oil, and Lard oil were selected as representative of classes A, B, C, D, and K, respectively. These materials were used to ignited fire flames for a total of 150 video clips which included multiple fire flames with a hot object in each video clip, and there exist 75 flame boundaries per each fuel class. Some examples of thermal video frames are shown in Table 4 which included more than one fuel class. The fire flame boundaries detected by our proposed method and examples of video sequences for fuel class classification are shown in Tables 5 and 6, respectively. Fire detection, which would be done all the time, was performed in experiments, and evaluation results are shown by comparison with conventional methods in Table 7. The fuel class classification using some existing machine learning tools such as bidirectional long shortterm memory (BiLSTM), long short-term memory (LSTM), was performed in varying per cents for training and testing, and the results are shown in Table 8. In addition, classification errors in all classes are shown in Table 9.

Table 3: *Experimental specification.*

Part	Devices/Software	Specification
Hardware	Computer	CPU: Intel Core i7-9700K GPU: Nvidia GeForce RTX 2060 Memory Size: 16 GB DDR4 Solid state drive: 512 GB
	Thermal camera	FLIR one pro and FLIR i3
Software	MATLAB	R2019b
Fuel	Class A	Paper, Plastic and Wood
	Class B	Alcohol, Gasoline, and Diesel
	Class C	VFF, AWG and VSF
	Class D	Magnesium
	Class K	Palm oil, Coconut oil and Lard oil
Data	Thermal video	seven frames per second

Fig. 13: *Environment set up for experiments.*

Table 4: *Examples of thermal video frames in experiments.*

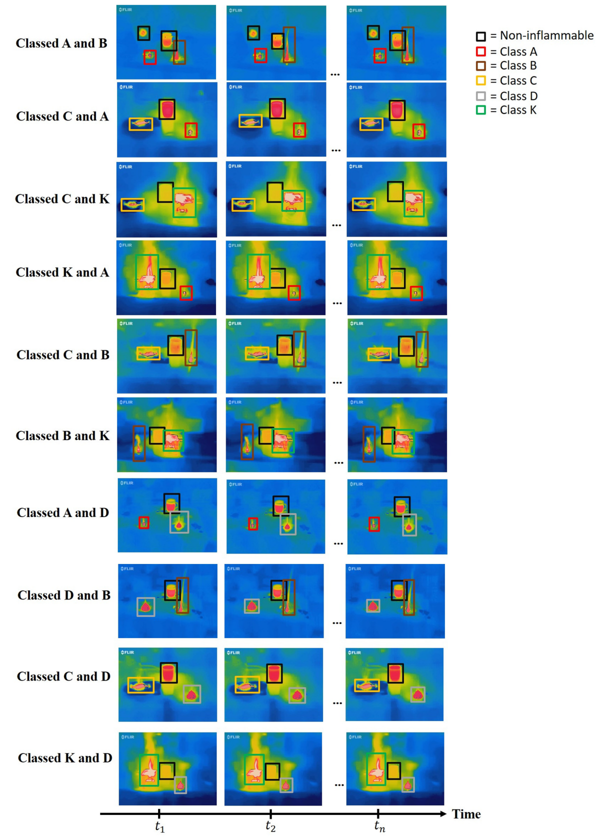


Table 5: *Extracted samples of fire boundaries in experiments.*

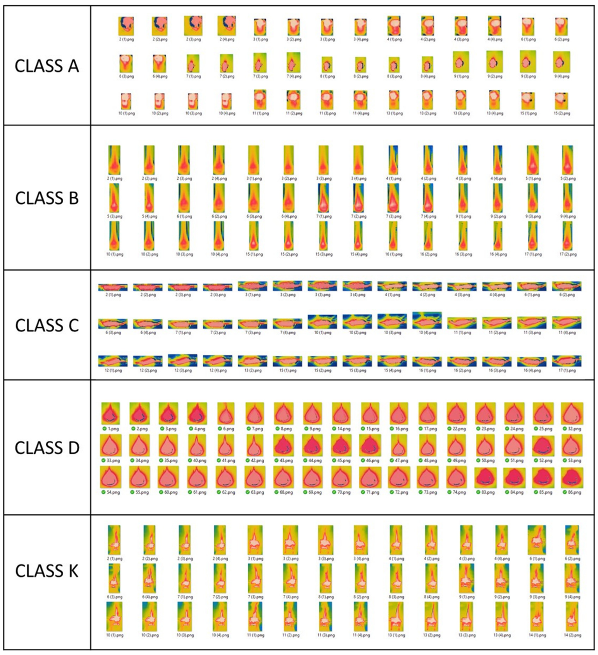


Table 6: *Examples of fire flames used for training and testing.*

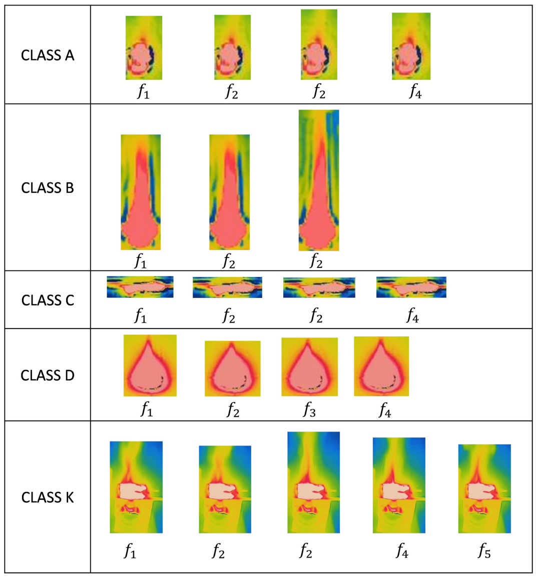


Table 7: *Accuracy of fire detection compared with conventional methods.*

Technique	Image Input	Methods	False Positive (%)	False Negative (%)	Accuracy (%)
Decision based	Thermal	Proposed method	6.67	0.00	93.33
	RGB	Rafiee et al. [17]	17.65	7.14	74.20
		Celik et al. [18]	29.41	0.00	83.87
		Chen et al. [19]	11.76	14.29	87.10
Learning based	RGB	Habibugle et al. [12]	5.88	14.29	90.32
		Di Lascio et al. [13]	13.33	0.00	92.86
		Foggia et al. [11]	11.67	0.00	93.55
		Khan Muhammad et al. [9]	8.87	2.12	94.50
		Khan Muhammad et al. [10]	0	0.14	95.86
		Arpit Jadon et al. [14]	1.23	2.25	96.53
		Byoungjun et al. [8]	2.47	1.38	97.92

Table 8: *Classification results obtained by classifiers.*

Training (%)	Testing (%)	BiLSTM	SD	LSTM	SD
90	10	90.13	0.086	90.74	0.071
80	20	89.54	0.062	89.97	0.051
70	30	88.56	0.062	88.32	0.074
60	40	87.56	0.075	88.22	0.063
50	50	87.20	0.065	86.79	0.070

6. DISCUSSION

Based on the proposed method using the heat information for fuel prediction, the system practically monitors and detects fire flame in an indoor environment. The proposed method utilizes heat change patterns to detect the fire flame, which is different from conventional methods using brightness information.

The advantage of heat-change information usage is to be able to detect fire, especially in a dark environment without light. In our experiments with a cup of hot coffee with high temperature, the proposed method could detect fire flame boundaries without picking up the boundary of coffee due to less heat change. It meant the proposed method can deal with fire flame in the environment including some high temperature objects. To compare with conventional methods using brightness information, although our proposed fire detection method using heat information was not able to get the best accuracy, it could achieve as high as 93.33% accuracy without false negatives, as shown in Table 7. The 6.67% of fire detection errors produced by our proposed method analytically were false positives. This practically meant we detect suspicious fire flames and ensured more reliability for fire detection. The advantage of our fire detection method is that it can deal with the fire cases in not only light but also a dark environment due to the usage of heat change information.

As the main objective of our proposed method which is assumed to be applied for automatic extinguishers in indoor environments, fuel of fire flames in multiple boundaries in an image would be classified into fuel classes (A-D and K), and a fire extinguisher is expected to be selected appropriately based on the fire flame class. As shown in Table 8, our proposed method using LSTM achieved fire flame classification in each boundary in as high as 92% accuracy with low standard deviation. The results proved the proposed method can be applied in fire fuel classification in each boundary for fire extinguishers. Although the research problem has been established for solving multiple isolated boundaries with different fuel classes as a merit of the proposed method, overlapping boundaries of different fuel classes were not solved in this paper, and should be considered as future work.

The classification errors were analyzed in a confusion matrix, as shown in Table 9. Most samples in experiments were successfully classified into fuel class, and an appropriate extinguisher might be selected for extinguishment, as shown by highlighted cells in a diagonal direction of the matrix. Errors located in the cells outside the diagonal direction were analyzed, and analysis results based on those error causes are divided into 12 groups, as shown in Table 10. Some fire flames look like others in term of features, and the scores in the last column indicate the mistakes of the classification. Although these are counted as minority compared with the whole number of experimental samples, feature design for classification should be reconsidered to improve this in future work. Furthermore, in the last four rows which reveal analysis of non-fuel as mistaken classification results, it is observed there exist a couple of classes which got high scores in the top level, but still less than the thresholding value. The thresholding method also should be reconsidered for solving this problem as another topic of future work.

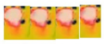
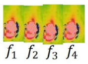
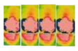
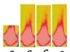
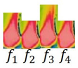
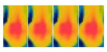
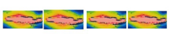
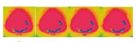
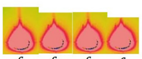
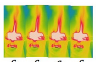
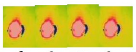
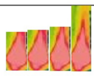
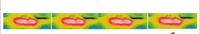
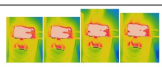
Table 9: *Classification errors in all fuel classes.*

Actual \ Predicted	Class A	Class B	Class C	Class D	Class K	Non-Fuel
Class A	84.57%	5.33%	1.33%	2.85%	0.57%	5.35%
Class B	5.52%	90.28%	0%	1.52%	0.38%	2.3%
Class C	0%	0%	94.47%	4%	0%	1.53%
Class D	1.71%	2.47%	4.38%	85.14%	0.19%	6.11%
Class K	0%	0.37%	0%	0%	99.24%	0.39%

7. CONCLUSION

It is important to detect fire in an early stage and extinguish the fire by an appropriate extinguisher as soon as possible. For an automatic fire-extinguishing system in an indoor environment, the system needs to automatically detect fire, classify the fuel for selecting a suitable distinguisher, and immediately extinguish the fire in an early stage. This paper proposed a method of fuel prediction based on heat information for an intelligent fire extinguisher in an indoor environment. While a fire flame rises rapidly according to the fuel type and expands to give damage to property in the early stage, heat and temperature simultaneously increase and are observed to be different based on fuel types. The increment of heat can be first used to detect early-stage fire, and then fire flame changes are considered to classify fuel type for automatic extinguisher selection. These form our basic concept. The concept can be implemented on a system using heat sensor, and thermal video as input data from the sensor would be employed to detect fire and classify fuel type in the case of fire occurrence. Although some warm things such as a cup of coffee and so on are in a high temperature level which is suspiscious to be detected as fire, fire in the early stage will be simply detected by immediate changes of heat in the indoor environment. The detected fire, which may increase rapidly, is subsequently used to classify fuel type based on the change pattern of the fire flame. For evaluation of the proposed method, experiments with fire have been performed with some fuel samples in classes based on NFPA fuel-class standard, and the results showed acceptable performance.

Table 10: *Analysis of classification errors.*

Mistakes of	Segmented fire flame boundaries	Classification Score
Class A as Class K	 f_1 f_2 f_3 f_4	Class A = 0.121 Class B = 0.005 Class C = 0.001 Class D = 0.001 Class K = 0.872
Class A as Class B	 f_1 f_2 f_3 f_4	Class A = 0.260 Class B = 0.725 Class C = 0.003 Class D = 0.002 Class K = 0.010
Class A as Class C	 f_1 f_2 f_3 f_4	Class A = 0.172 Class B = 0.001 Class C = 0.824 Class D = 0.002 Class K = 0.001
Class A as Class D	 f_1 f_2 f_3 f_4	Class A = 0.139 Class B = 0.002 Class C = 0.001 Class D = 0.853 Class K = 0.005
Class B as Class A	 f_1 f_2 f_3 f_4	Class A = 0.773 Class B = 0.224 Class C = 0.001 Class D = 0.001 Class K = 0.001
Class B as Class K	 f_1 f_2 f_3 f_4	Class A = 0.001 Class B = 0.270 Class C = 0.001 Class D = 0.001 Class K = 0.727
Class B as Class D	 f_1 f_2 f_3 f_4	Class A = 0.001 Class B = 0.110 Class C = 0.001 Class D = 0.734 Class K = 0.155
Class C as Class D	 f_1 f_2 f_3 f_4	Class A = 0.001 Class B = 0.001 Class C = 0.106 Class D = 0.891 Class K = 0.001
Class D as Class A	 f_1 f_2 f_3 f_4	Class A = 0.802 Class B = 0.004 Class C = 0.040 Class D = 0.153 Class K = 0.001
Class D as Class B	 f_1 f_2 f_3 f_4	Class A = 0.033 Class B = 0.856 Class C = 0.001 Class D = 0.109 Class K = 0.001
Class D as Class C	 f_1 f_2 f_3 f_4	Class A = 0.020 Class B = 0.007 Class C = 0.885 Class D = 0.087 Class K = 0.001
Class D as Class K	 f_1 f_2 f_3 f_4	Class A = 0.001 Class B = 0.004 Class C = 0.001 Class D = 0.206 Class K = 0.788
Class K as Class B	 f_1 f_2 f_3 f_4	Class A = 0.001 Class B = 0.984 Class C = 0.001 Class D = 0.001 Class K = 0.015
Class A as Non-fuel	 f_1 f_2 f_3 f_4	Class A = 0.557 Class B = 0.441 Class C = 0.001 Class D = 0.001 Class K = 0.001
Class B as Non-fuel	 f_1 f_2 f_3 f_4	Class A = 0.304 Class B = 0.693 Class C = 0.001 Class D = 0.001 Class K = 0.001
Class C as Non-fuel	 f_1 f_2 f_3 f_4	Class A = 0.001 Class B = 0.001 Class C = 0.679 Class D = 0.001 Class K = 0.318
Class D as Non-fuel	 f_1 f_2 f_3 f_4	Class A = 0.085 Class B = 0.001 Class C = 0.242 Class D = 0.671 Class K = 0.001
Class K as Non-fuel	 f_1 f_2 f_3 f_4	Class A = 0.384 Class B = 0.025 Class C = 0.001 Class D = 0.003 Class K = 0.586

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Teerapong Suejantra received an B.Eng. degree in Electronic engineering technology from King Mongkut's University of Technology North Bangkok in 2017, respectively. He is currently pursuing the M.Eng. in Electronic and Telecommunication Engineering with the King Mongkut's University of Technology Thonburi. His current research interests include computer vision, image processing, fire detection, Fuel prediction and machine learning.

Kosin Chamnongthai (S'85–M'87–SM'91) received a B.Eng. degree in applied electronics from the University of Electro-Communications, Tokyo, Japan, in 1985, a M.Eng. degree in electrical engineering from the Nippon Institute of Technology, Saitama, Japan, in 1987, and a Ph.D. degree in electrical engineering from Keio University, Tokyo, in 1991. He is currently a Professor with the Electronic and Telecommunication Engineering Department, Faculty of Engineering, King Mongkut's University of Technology Thonburi. His research interests include computer vision, image processing, robot vision, signal processing, and pattern.