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Real-time probabilistic classification of fire and smoke using thermal imagery for intelligent firefighting robot

Jong-Hwan Kim*, Brian Y. Lattimer

Virginia Tech, Mechanical Engineering Department, Blacksburg, VA, USA

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ABSTRACT

A real-time probabilistic classification method was developed for identifying fire, smoke, their thermal reflections, and other objects in infrared images. This algorithm was formulated for use on a robot that will autonomously locate fires inside of a structure where the fire is outside the robot field of view. Thermal images were used to extract features due to the fact that long wavelength infrared is capable of imaging through zero visibility environments. For an autonomous navigation under fire environments, robots need to be able to differentiate between desired characteristics, such as fire and smoke, and those that may lead the robot in the incorrect direction, such as thermal reflections and other hot objects. The probabilistic classification method in this paper provides a robust, real-time algorithm that uses thermal images to classify fire and smoke with high accuracy. The algorithm is based on four statistical texture features identified through this work to characterize and classify the candidates. Based on classification of candidates from large-scale test data, the classification performance error was measured to be 6.8% based on validation using the test dataset not included in the original training dataset. In addition, the precision, recall, *F*-measure, and *G*-measure were 93.5–99.9% for classifying fire and smoke using the test dataset.

1. Introduction

There has been interest in using robots to support firefighters in order to reduce firefighter deaths and increase their effectiveness on the job. Various sizes and shapes of firefighting robots have been developed for outdoor and indoor purposes [1–6]; however, most of them are remotely controlled by operators. Recently, a shipboard autonomous firefighting robot (SAFFiR) program, prototype is illustrated in Fig. 1, is being developed to locate and suppress fires inside ships and structures. Through the SAFFiR program, further advancements of artificial intelligent algorithms/perception systems [7–11] and unmanned fire suppression systems [12] have been developed to enhance autonomous firefighting robots.

One such task is locating a fire inside of a structure that is not in the direct field of view (FOV) of the robot. This involves using features (e.g., presence of smoke, flames) in the FOV of the robot to determine a heading that will ultimately lead the robot to the fire so that it can suppress it. Many conventional detection systems will effectively indicate the presence of a fire inside the structure [13–15], but takes a long response in large spaces [16] and do not provide sufficient data for fire locating. Extracting fire and smoke features from an environment has been explored for advanced detection systems [17–21]. However, the existing fire and smoke detection methods [17,19,20,22–25] have practical limitations that make them not directly applicable for use on a dynamic robot.

Vision systems using RGB cameras have been widely used for fire (or smoke) detection due to their low weight, low power consumption and large FOV that includes color, shape, motion and texture information. The majority of these applications use fixed location surveillance cameras for smoke and fire detection. RGB image databases online are used to support algorithm development [26–28]. Camera-based methods reported in Refs. [18,20,24,25,29,30] are not applicable to firefighting robots due to the high false positive rate from colors or reflection illuminations similar to that with fire [23]. Due to the fact that RGB cameras may operate in the visible to short wavelength infrared (IR) (less than 1 μm), they are not usable in smoke-filled environments where the visibility has sufficiently decreased [10,23]. In addition, because the performance of the cameras depends on light, these methods cannot provide proper information under local or global darkness, e.g. shadows or darkness caused by damaged lighting.

Handheld thermal infrared cameras (TIC) are typically used to aid in firefighting tasks within smoke-filled environments [31–34]. Due to the fact that TICs absorb infrared radiation in the long wavelength IR (7–14 μm), they are able to image surfaces even in

* Corresponding author.
E-mail address: hspkorea@vt.edu (J.-H. Kim).

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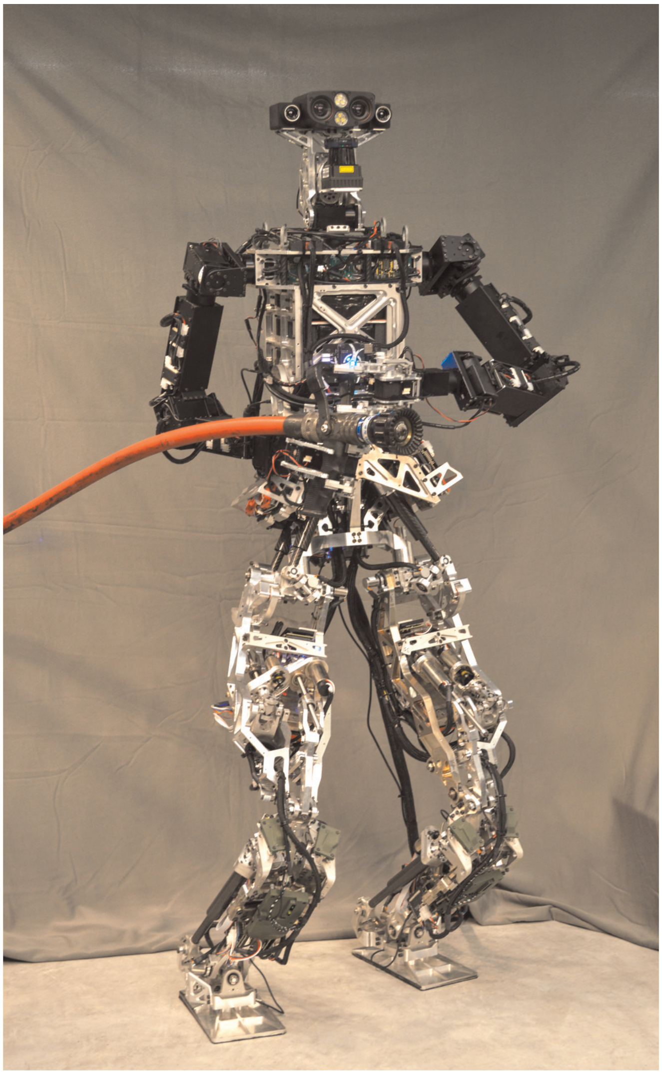

Fig. 1. The shipboard autonomous firefighting robot (SAFFiR). Credit "Photo by : Eric Hahn and Coleman Knabe"

dense smoke and zero visibility environments [10,23]. TICs produce gray scale images; therefore, online RGB image databases cannot be used to support development of feature extraction and classification algorithms [26–28]. Studies [16,29,35] have investigated the use of thermal images for fire detection however simultaneous classification of fire, smoke, and their thermal reflections in indoor fire environments has not been completed for fire locating.

The vision system onboard a robot will contain cameras that are moving due to the dynamics of the robot itself. As a result, there are limitations in using methods that incorporate relative motion features from a stationary camera [17–21]. In a previous study conducted on locating fires using thermal images [9], there were problems distinguishing between fire reflections and an actual fire as well as smoke reflections and smoke when they appeared together in the FOV. Due to this, erroneous robot headings were provided which led the robot in the wrong direction during navigation. Existing research on binary classification, which classifies fire from a non-fire object [18,23,24] or smoke and non-smoke object [17,22,36], has not been able to distinguish fire and smoke from their reflections or classify fire, smoke, and reflections simultaneously. A real-time classification is needed to make the robot accurately analyze local environments and autonomously decide where to move for fire location even outside the FOV.

This paper presents a probabilistic classification method for fire, smoke, their thermal reflections, and other hot objects (i.e., not fire, smoke, or reflections). The method uses images from a single thermal infrared camera mounted on a robot and acquires textural features to recognize patterns while minimizing the influence of dynamic robot motion. Bayes' theorem was used to compute the posterior probabilities of the fire, smoke, thermal reflections, and other object classes, which can be used to analyze local environments for navigating toward the fire. For reliability, the method was trained using large-scale fire test data having a range of temperature and smoke conditions. The real-time algorithm was then tested using a separate series of tests to validate its ability to accurately classify the fire environment.

2. System architecture

Fire, smoke, their thermal reflections and other objects (i.e., not fire, smoke, or reflections) are probabilistically classified to provide SAFFiR with information to determine a proper heading and autonomously navigate toward a fire that is outside the robot FOV. As illustrated in Fig. 2, the proposed method consists of extracting relevant candidates in the scene and probabilistically classifying the candidates based on statistical texture features. Images for analysis were taken using a FLIR A35 long wavelength infrared (7–14 μm) camera with a 320×256-pixel focal plane array, 60 Hz frame rate that produces 14 bit images with intensity ranges between $-16{,}384$ for $-40\,°C$ and -1 for $160\,°C$. This particular camera was used since it is lightweight and can image in clear as well as zero visibility fire smoke conditions. Candidates from the images that have the highest likelihood to be fire, smoke, or reflections are extracted from the scene by adaptive background subtraction and morphological filtering. However, it is difficult to distinguish fire and smoke from their reflections through these methods alone, and this may cause erroneous headings leading the robot in the wrong direction during navigation. To overcome this, Bayesian classification was performed to probabilistically distinguish fire and smoke from their reflections by analyzing multiple texture features extracted from the candidates. Extracted candidates that are determined to not be fire, smoke, or thermal reflections are labeled as other objects. Adaptive histogram equalization [37]and colored ellipse overlay were applied to produce final images.

3. Pre-processing

3.1. Adaptive background subtraction

Existing research [17–21,38] uses color and/or motion-based background subtraction from a stationary camera to detect the foreground, which contains the candidates of interest. However, these approaches are not compatible with this research because color information is not available in thermal images and retrieving relative motion from robot in motion creates a large amount of noise that results in extensive computation for motion compensation. One of the main characteristics of fire and smoke is that they are higher in temperature than the background. With temperature related to intensity in the thermal image, fire and smoke regions appear brighter than the background. As a result, intensity is a primary factor when subtracting the foreground from the background.

The intensity histogram from a thermal image changes as the surrounding environment of a fire changes. As a result, manual thresholding and parametric modeling techniques are less efficient because they require continual updating to find the optimum