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AUTOMATED FOREST FIRE DETECTION USING FUZZY LOGIC BASED IMAGE PROCESSING METHOD

БҰЛЫҢҒЫР ЛОГИКА НЕГІЗІНДЕГІ БЕЙНЕЛЕРДІ ӨҢДЕУ ӘДІСІН ОРМАН ӨРТТЕРІН АВТОМАТТЫ ТҮРДЕ АНЫҚТАУДА ҚОЛДАНУ

АВТОМАТИЗИРОВАННОЕ ОБНАРУЖЕНИЕ ЛЕСНЫХ ПОЖАРОВ С ИСПОЛЬЗОВАНИЕМ МЕТОДА ОБРАБОТКИ ИЗОБРАЖЕНИЙ НА ОСНОВЕ НЕЧЕТКОЙ ЛОГИКИ

Abstract. *Wildfires and the extent of the damage and destruction they leave behind are well known. Due to the limitations of manual methods for monitoring fires, there is an urgent need to develop automated methods for them. In recent years, there has been significant development of vision systems for fire detection. This article presents a method for identifying fire and smoke using fuzzy logic image processing to achieve efficient and early detection of forest fires. The fuzzy logic-based fire detection method is designed to detect and segment areas of flame and smoke in visual images captured by a camera on board an unmanned aerial vehicle (UAV). The model has been tested on a wide range of aerial images containing areas of fire and smoke and has shown good performance up to 95 % accuracy.*

Keywords: *Fuzzy logic, fire detection, image processing, forest fires.*

Аңдатпа. *Дала өрттері және олардың артта қалдырған зияны мен жойылу ауқымы белгілі. Өртті бақылаудың қолмен әдістерінің шектеулеріне байланысты олар үшін автоматтандырылған әдістерді әзірлеудің шұғыл қажеттілігі бар. Соңғы жылдары өртті анықтау үшін техникалық көру жүйелерінің айтарлықтай дамуы байқалды. Бұл мақалада дала өрттерін тиімді және ерте анықтауға қол жеткізуге арналған анық емес логикаға негізделген кескінді өңдеу арқылы от пен түтінді анықтау әдісі берілген. Бұлыңғыр логикаға негізделген өртті анықтау әдісі ұшқышсыз ұшу аппаратының (ҰҰА) бортында камера түсірген визуалды кескіндердегі жалын мен түтін аймақтарын анықтауға және сегменттеуге арналған. Модель от пен түтін аумақтары бар аэрофотосуреттердің кең ауқымында сыналған және 95% дәлдікке дейінгі өнімділікті көрсетті.*

Түйін сөздер: *Бұлыңғыр логика, өртті анықтау, кескінді өңдеу, орман өрттері.*

Аннотация. *Лесные пожары и масштабы ущерба и разрушений, которые они оставляют после себя, хорошо известны. В связи с ограничениями ручных методов мониторинга пожаров существует острая необходимость в разработке для них автоматизированных методов. В последние годы наблюдается значительное развитие систем технического зрения для обнаружения пожара. В этой статье представлена метод для идентификации огня и дыма с использованием обработки изображений на основе нечеткой логики, предназначенный для достижения эффективного и раннего обнаружения лесных пожаров. Метод обнаружения пожара на основе нечеткой логики предназначен для обнаружения и сегментации областей пламени и дыма на визуальных изображениях, снятых камерой на борту беспилотного летательного аппарата (БПЛА). Модель была протестирована на большом количестве аэрофотоснимков, содержащих участки ог-*

ня и дыма, и показала хорошие результаты с точностью до 95 %.

Ключевые слова: *Нечёткая логика, обнаружение пожара, обработка изображений, лесные пожары.*

Introduction. Every year there are many forest fires, devastating millions of hectares of forest. In addition to destroying flora and fauna, these fires also destroy infrastructure and, unfortunately, sometimes result in loss of life among firefighters and civilians who may be accidentally surrounded by fire. For countries where forests cover a significant area, such as Kazakhstan, forest fires are a national problem. Although Kazakhstan is a sparsely forested country, the area of the forest fund (the totality of all forests and forestry lands) is 30.4 million hectares, of which 13.3 million hectares are covered with forests (11% of the country's territory). Up to 1000 forest fires with a total area of up to 100 thousand hectares are registered annually. According to the Ministry of the Republic of Kazakhstan, in 2021 alone, about 1000 fires were registered in Kazakhstan, the material damage from which amounted to more than 6 billion tenge, and the forest area destroyed by fire amounted to 167 thousand hectares [1]. Obviously, for many countries of the world with significant forest resources, including Kazakhstan, it is important to detect a fire as early as possible, determine its exact location and eliminate it. Therefore, there is an urgent need to develop automated methods of fire reconnaissance. Existing technological limitations need to be extended to detect and track fires in the early stages of fires. Thus, monitoring and early detection of fires are two key factors that allow firefighters to act appropriately without allowing fires to run wild.

In recent years, an unmanned aerial vehicle (UAV) have become increasingly important for environmental monitoring, on the one hand, providing data from remote and hard-to-reach areas, and on the other hand, reducing the cost of conducting the necessary research using traditional field methods, while increasing work efficiency. The use of UAVs as part of firefighting complexes solves a number of problems associated with a lack of personnel, inaccessibility of territories, the need to minimize the impact of human presence, and determine operational data on fire during forestry work. On-board cameras and sensors can provide a view of a forest fire from various heights. Unmanned aerial systems can serve as "eyes in the sky" for firefighters and help to locate fires more accurately, which can significantly improve the effectiveness of forest fire fighting. Thermal imaging and more sophisticated sensor systems can greatly increase payloads, so techniques need to be developed that can be used with lightweight surveillance cameras aboard these vehicles. The most important part of the development of monitoring systems using cameras installed on UAVs is fire detection on video images using machine vision methods and algorithms. Typically, in fire conditions, smoke appears before flames, and therefore it is important to identify the smoke for early fire detection. Smoke invariably covers most of the airspace around a burning forest. In aerial photographs, most often the fire is hidden behind a thick cover of smoke, and therefore the automatic identification of smoke along with the fire becomes important for complete situational awareness. Color is one of the main criteria for detecting fires and is used in most of the currently available methods for detecting fires from digital images. Typically, chromatic image analysis uses one or more decision rules in certain color spaces to find areas with fire colors. Often used color models are RGB (red, green, blue), HSV (Hue, Saturation, Value), HSI (Hue, Saturation, Intensity), YCbCr (brightness, chroma, blue, chroma, red) and others. In the case of organic materials such as trees and bushes, fire has a well-known red-yellow color. Many natural objects have a color similar to fire and can often be mistaken for flames. For this reason, it is very important to distinguish such false alarm situations from real fire. For smoke in the early stages of a fire, when the temperature of the smoke is low, the smoke is expected to have color characteristics ranging from bluish-white to white. Gradually, as the fire intensifies, the temperature of the smoke increases and changes color from black-grayish to black. Because this work uses information about smoke in the early stages of fire for analysis, it is important that smoke samples be obtained when the smoke is at a low temperature. This is the case when the smoke samples have color characteristics ranging from white-bluish to white.

Most of the studies in fire detection through image processing have focused on using both chromatic and dynamic fire attributes to identify. Many fire detection methods use color as the main feature for detecting a fire in a video sequence [2-5]. Such methods are efficient (low complexity) but prone to false positives as the color of the fire changes depending on several variables. Time information, analysis of turbulence and periodicity around the boundaries of objects can partially overcome these shortcomings [6]. The wavelet transform is another tool that can improve the reliability of detection [7], as well as fuzzy logic [8], [9]. In the study [9] authors use a fuzzy model to distinguish fire areas in a frame using color recognition. The classic Mamdani fuzzy inference process allows us to estimate the degree to which each pixel belongs to the set of fire-colored pixels. The method provides on average the best hit rate (about 87%) and gives a very low number of false negatives.

Color remains the primary function for the correct classification of fire pixels and is used in almost all detection methods. Traditional fire detection uses RGB (Red, Green, Blue), HSV (Hue, Saturation, Value), HSI (Hue, Saturation, Intensity), and YCbCr (Luminance, Blue component and Red component) and others. For example, the RGB and HSV models are used to create three decision rules for candidate region detection [10], [11]. In papers [12], [13], the YCbCr color space is used for the general model and proposes various rules for accurate detection. Singh and Deb used the rules of multicolor features based on the YCbCr color space to detect fire pixels in a video sequence [14]. This method works great for detecting fire areas in real fire video sequences. Chen et al. proposed a smoke detection algorithm based on video processing for a fire early warning system [15]. The algorithm is based on static and dynamic decision criteria. The static decision is based on the grayish color of the smoke, while the dynamic decision rule is based on the characteristics of smoke propagation such as smoke disorder and smoke growth rate. The grayish color is described by the intensity component of the HSI color system, because among the various color models, the HSI color model is very suitable for providing a more human-oriented way of describing colors, because the hue and saturation components are closely related to how people perceive color. This paper is devoted to the detection of areas of fire and smoke in images obtained in the early stages of a fire, using image processing methods based on fuzzy logic. The proposed method of image processing based on fuzzy logic, which allows to automatically identify fire and smoke in visual images. The effectiveness of the identification algorithm has been demonstrated on a number of real aerial images of fires.

Experimental. Fuzzy logic begins with the concept of a fuzzy set. A fuzzy set is a collection of elements of an arbitrary nature, with respect to which it is impossible to say exactly whether these elements have some characteristic property that is used to define a fuzzy set. It can only contain elements with a partial degree of membership. In fuzzy logic, the truth of any statement becomes a matter of degree. The main advantage that fuzzy reasoning offers is the ability to answer a yes-no question with a not-quite yes or no answer. People think this way all the time, but it's a fairly new technique for computers. Fuzzy logic reasoning is a superset of standard logic, so if fuzzy values are at the extremes 1 (completely true) and 0 (completely wrong), standard logic operations will be performed. If true is set to the numeric value 1 and false is set to the numeric value 0, this value indicates that the fuzzy logic also accepts intermediate values such as 0.8 and 0.865.

A fuzzy inference system is a process of obtaining fuzzy conclusions about the required control of an object based on fuzzy conditions or prerequisites, which are information about the current state of the object. This process combines all the basic concepts of fuzzy set theory: membership functions, linguistic variables, fuzzy implication methods, etc. The development and application of fuzzy inference systems include a number of stages (see Figure 1).

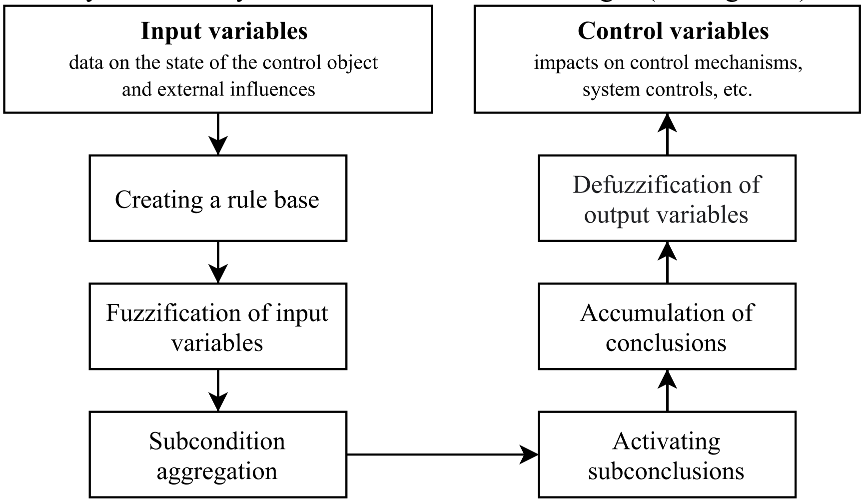


Figure 1. Fuzzy inference process diagram

In general, the two most popular fuzzy inference systems are available: the Mamdani fuzzy model and the Sugeno fuzzy model. Sugeno fuzzy inference, also called Takagi-Sugeno-Kanga fuzzy inference, uses singleton output membership functions that are either constant or linear functions of the input values. The Sugeno system uses the weighted average or weighted sum of multiple data points rather than calculating the center of gravity of a 2D region. And in the Mamdani system, the result of each rule is a fuzzy set. Because Mamdani systems have more intuitive and easier to understand rule bases, they are well suited for expert system applications where rules are created based on human expertise, such as medical diagnostics. The result of each rule is a fuzzy set obtained from the output membership function. These output fuzzy sets are combined into one fuzzy set using the aggregation method of the fuzzy inference system. Then, to calculate the final crisp output value, the combined output fuzzy set is defuzzified using image classification techniques. The advantage of this model is that the rule base is usually provided by an expert and is therefore, to a certain extent, defying explanation and learning. Because of its simplicity, the Mamdani model is still the most commonly used technique for solving many real-world problems [16].

The block diagram of the system based on fuzzy logic used in this study is shown in Figure 2. The fuzzy logic system transforms crisp input data into crisp output data. Once the rules are in place, the system can be viewed as a mapping of inputs to outputs, and this mapping can be quantified by the function $y = f(x)$. Rules can be extracted from numerical data or provided by experts. Engineering rules are expressed as a set of IF-THEN statements.

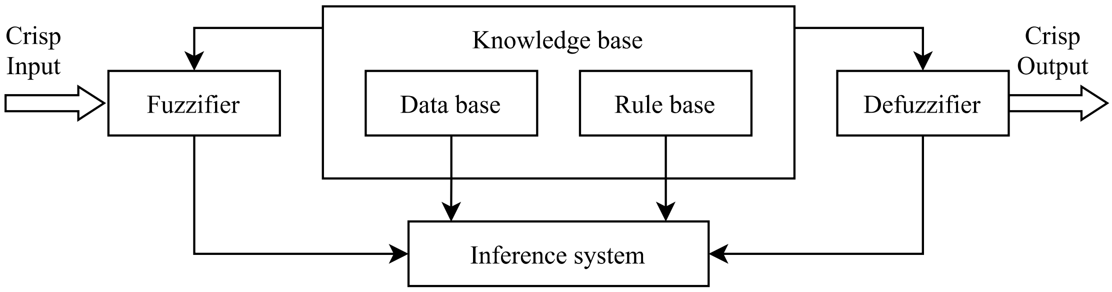


Figure 2. Structure of Fuzzy Rule Based System

A system based on fuzzy rules consists of four parts: a fuzzifier, a knowledge base, an inference system, and a defuzzifier [17]:

1) Fuzzifier: A fuzzifier converts hard numbers to fuzzy values. Fuzzification is performed based on the type of inference mechanism or inference strategy, such as disjunction or composition rules. This is necessary in order to activate the rules associated with fuzzy sets. In the literature, the input to a fuzzifier is referred to as crisp input because it contains accurate information about specific parameter information. The fuzzifier converts this exact value into the form of an inexact value like "small", "medium", "long", etc. with a degree of belonging to it, the value of which is in the range from 0 to 1.

2) Knowledge base: The main part of the fuzzy system is the knowledge base, which together mentions both the rule base and the database. A fuzzy knowledge base is a set of fuzzy rules of the form “IF <rule premise>, THEN <rule conclusion>”, which determine the relationship between inputs and outputs of a controlled object and/or expert system.

3) Inference system: The inference system and decision block perform inference operations according to the rules. In the fuzzy inference system, the principles of fuzzy logic are used to combine fuzzy rules into a mapping of input fuzzy sets to output fuzzy sets. Just as people use many different types of inference procedures to help understand things or make decisions, there are many different types of inference procedures based on fuzzy logic.

4) Defuzzification is the process of converting a set of controller output values into a single point value and performing a renormalization of the output data that maps the controller output point value to its physical area. The output generated by an output block is always fuzzy. The defuzzifier's job is to take fuzzy input and provide real-world output.

Development of flame detection rules based on fuzzy logic. Among the various color systems, the HSI color model is very human-friendly because the hue, saturation, and value components are closely related to how people perceive color. HSI describes a color space using hue, saturation, and intensity, and compared to RGB, HSI is more suitable for modeling the color perception properties of the human visual system, since the hue and saturation components are closely related to how people perceive color.

According to the analysis of the fire features, the hue values for fire from 0 to 70 correspond to the red-yellow range. The saturation value obtained in brighter conditions is greater than in darker scenes, as this is affected by the backlight. In the absence of other background lighting, the fire will become the main and only source of illumination. In order to guarantee sufficient brightness during video processing, the intensity must be above a certain threshold. Therefore, HSI-based rules are used as the second part of flame detection from chromatic data, which can be described as follows (1):

$$\begin{aligned} &0 \le H \le 70 \\ &50 \le S \le 150 \\ &120 \le I \le 255 \end{aligned} \tag{1}$$

where H, S, and I are the hue, saturation, and intensity components of the image, respectively.

To do this, we convert the image from the RGB color space to HSI, which starts with normalizing the RGB value [18]:

$$r = \frac{R}{R+G+B},\ g = \frac{G}{R+G+B},\ b = \frac{B}{R+G+B}. \tag{2}$$

Each normalized component of H, S and I is then obtained using the following formulas (3)-(6):

$$h = \cos^{-1}\left\{ \frac{0.5 \cdot \left[(r-g) + (r-b) \right]}{\left[(r-g)^2 + (r-b)(g-b) \right]^{1/2}} \right\} \quad h \in [0, \pi] \; for \; b \le g \tag{3}$$

$$h = 2\pi - \cos^{-1}\left\{ \frac{0.5 \cdot \left[(r-g) + (r-b) \right]}{\left[(r-g)^2 + (r-b)(g-b) \right]^{1/2}} \right\} \quad h \in [0, 2\pi] \; for \; b > g \tag{4}$$

$$s = 1 - 3 \cdot \min(r, g, b) \quad s \in [0, 1] \tag{5}$$

$$i = \frac{R+G+B}{3 \cdot 255} \quad i \in [0, 1] \tag{6}$$

For convenience, the values of h, s and i are converted in the range [0, 360], [0, 100], [0, 255] according to the formulas (7)-(9):

$$H_h = h \times 180 / \pi \tag{7}$$

$$H_s = s \times 100 \tag{8}$$

$$H_i = i \times 255 \tag{9}$$

Smoke segmentation method. The smoke of a fire does not have the characteristics of color as the flames of a fire. During the initial stage of a fire, the smoke will be bluish-white to white when the temperature of the smoke is relatively low. The more the temperature of the smoke increases, its color changes from dark gray to black-gray when it reaches the border of the start of ignition of the flame. Also, burning different materials can produce different amounts and colors of smoke. As a rule, the smoke has a grayish color, which can be divided into light gray and dark gray areas. In addition, based on the characteristics of the smoke, it can be assumed that the three smoke components in the RGB model are almost equal or have little difference. This phenomenon means that the absolute difference between the maximum and minimum values of these three components must be limited to a certain threshold. So, the first smoke detection rule can be set as the following system of equations (10), (11):

$$Ts = \max(Ts_1, Ts_2, Ts_3) \le T_{\max} \tag{10}$$

$$\begin{cases} |R(x,y) - G(x,y)| = Ts_1, \\ |G(x,y) - B(x,y)| = Ts_2, \\ |R(x,y) - B(x,y)| = Ts_3, \end{cases} \tag{11}$$

where Ts_1, Ts_2 and Ts_3 are calculated as the difference between each two channels. Ts – the maximum absolute difference between the three components of the RGB model, $T_{\max} \in [Ts_L, Ts_H]$ – a given global threshold for determining the similarity of the intensity of each RGB color channel, Ts_L and Ts_H - the lower and high limits of the threshold values.

To effectively describe the color of the smoke, the HSI color model is used, which is used to describe the light gray and dark gray areas in $\left[I_{Light_1}, I_{Light_2} \right]$ and $\left[I_{Dark_1}, I_{Dark_2} \right]$ respectively. Therefore, the following second smoke detection rule can be formulated:

$$I_{Low_1} \le I \le I_{Low_2}, \quad for\ light-gray\ color,$$
$$I_{Dark_1} \le I \le I_{Dark_2}, \quad for\ dark-gray\ color$$

where I – the intensity value of each pixel in the current frame, the choice of I_{Light_1} I_{Light_2}, I_{Dark_1} and I_{Dark_2} depends on the statistical data of the experiments.

Fuzzy smoke detection rules. The fuzzy logic method is considered one of the best options for real-time operation, high non-linearity and complex calculations. The triangle membership function is used for each input, and it can be mathematically written as the following system of inequalities (12) [19]:

$$f_{ij}(z_j) = \begin{cases} 1+(z_i-c_{ij})/b_{ij}^- & if \quad -b_{ij}^- \le (z_j-c_{ij}) \le 0, \\ 1-(z_i-c_{ij})/b_{ij}^+ & if \quad 0 \le (z_j-c_{ij}) \le b_{ij}^+, \\ 0, & otherwise \end{cases} \tag{12}$$

where *i* and j denote the number of inputs and triangle membership functions, respectively, z_j – the *j*-th input, c_{ij} – the *i*-th centroid, b_{ij}^- and b_{ij}^+ are represent the lower and upper half-widths of the *i*-th triangle membership function.

In addition, as one of the most popular defuzzification methods, the maximum-minimum value aggregation and centroid defuzzification method is used in this study to calculate the output value. In this study, only one output is defined in a fuzzy smoke detection system. Similar to the entry plan, the defuzzification rule for the exit is constructed as the following system of inequalities (13):

$$m_j(y) = \begin{cases} 1+(y-\gamma_j)/\beta_j^- & if \quad -\beta_j^- \le (y-\gamma_j) \le 0, \\ 1-(y-\gamma_j)/\beta_j^+ & if \quad 0 \le (y-\gamma_j) \le \beta_j^+, \\ 0, & otherwise \end{cases} \tag{13}$$

where $m_j(y)$, γ_j and *y* denote the *j*-th fuzzy output, modal point, and crisp number, respectively. β_j^- and β_j^+ are the lower and upper half-widths of the *j*-th inference rule, respectively.

Consider that the *j*-th rule is the result of $z_1 \in$ fuzzy set *i* and $z_2 \in$ fuzzy set *k*, the activation level of the consequence of the *j*-th rule can be represented as ω_j, then this activation level can be expressed as:

$$\omega_j = \min\left[f_{i1}(z_1), f_{k2}(z_2)\right]$$

where the fuzzy output is calculated by the formula (14):

$$m(y) = \sum_{j=1}^{M} \overline{m}(y). \tag{14}$$

Applying the chosen centroid defuzzification scheme, one can map a fuzzy output to a crisp number $\hat{y}$ as formula (15):

$$\hat{y} = \frac{\sum_{j=1}^{M} \omega_j C_j S_j}{\sum_{j=1}^{M} \omega_j S_j}, \tag{15}$$

where C_j and S_j are the centroid and the area of the *j*-th fuzzy membership function of the output, respectively. In addition, the centroid C_j can be defined as expression (16):

$$C_j = \frac{\int y m_j(y) dy}{\int m_j(y) dy}. \tag{16}$$

Results and discussion. The Fuzzy Logic toolkit in Matlab 9.5.0 (R2018b) is used to build a Mamdani-type fuzzy inference system. The computational time required to process an image with a resolution of 1024 x 1024 pixels on a 64-bit 3.6 GHz Intel Core I3-10100F processor is approximately 0.5 seconds per frame. The smoke detection capabilities add to the fire identification capability of this fuzzy model. The images are analyzed in color HSI, as it describes the image most closely to human vision. The input to the system is the S and I value of each pixel. We used a combination of triangular and trapezoidal membership functions for the difference between $S(x, y)$ and $I(x, y)$. Membership functions for each input and output are shown in Figure 3 – Figure 7.

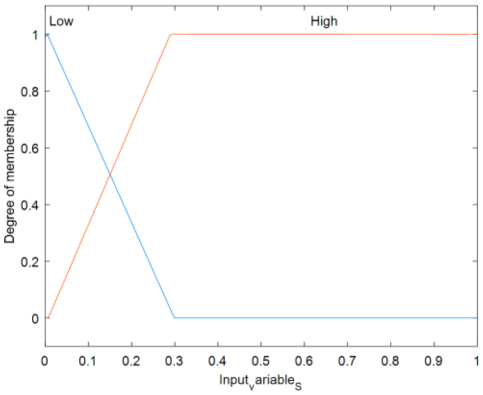


Figure 3. Membership function for input (S)

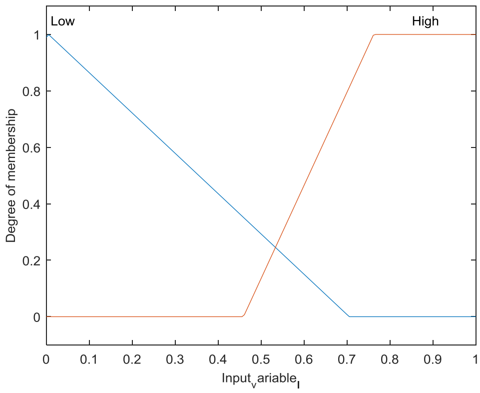


Figure 4. Membership function for input (I)

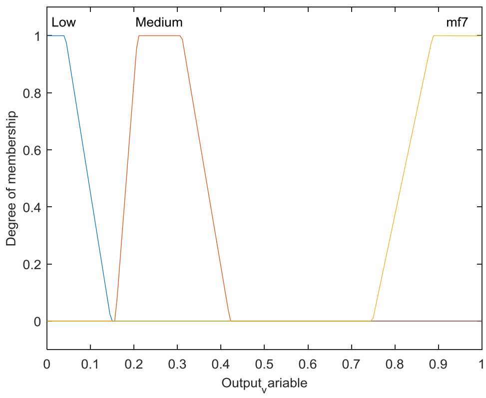


Figure 5. Membership function for output (fire)

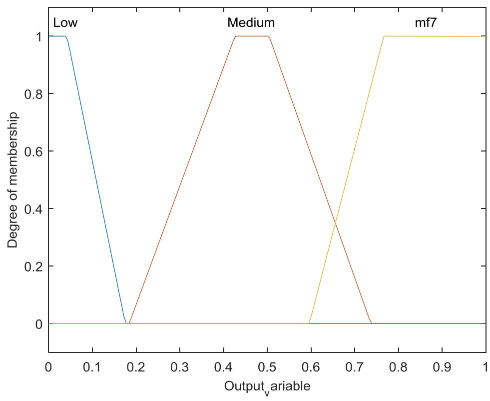


Figure 6. Membership function for output (smoke)

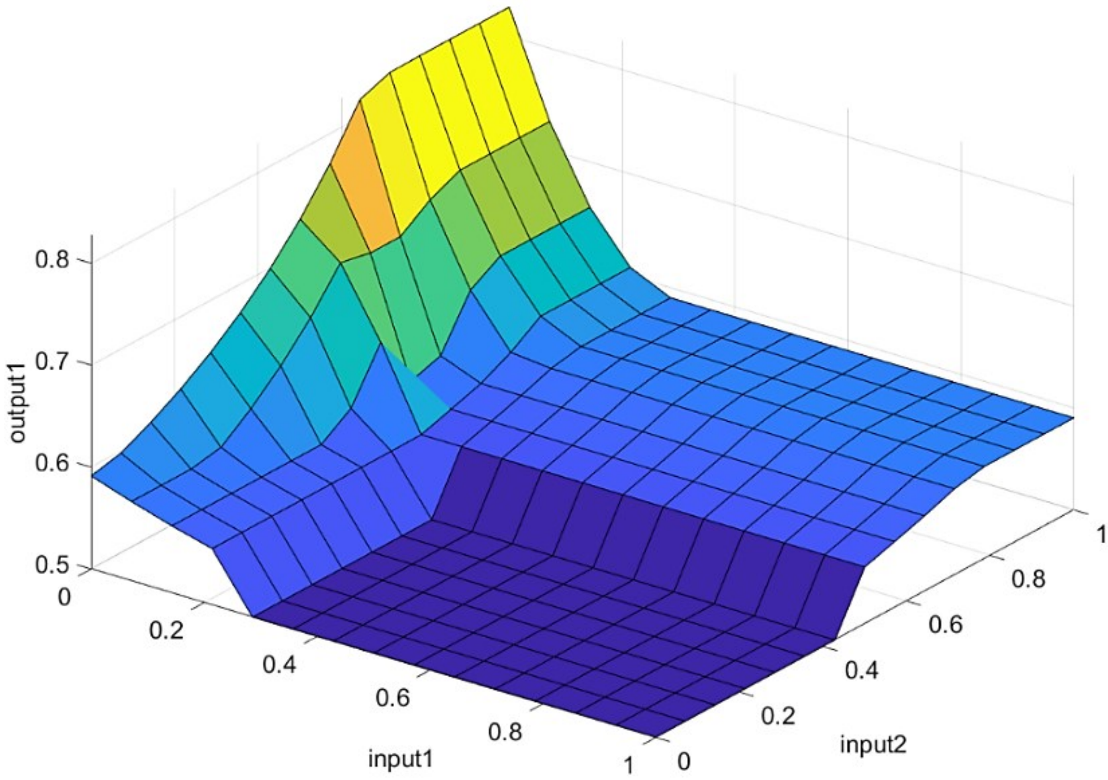
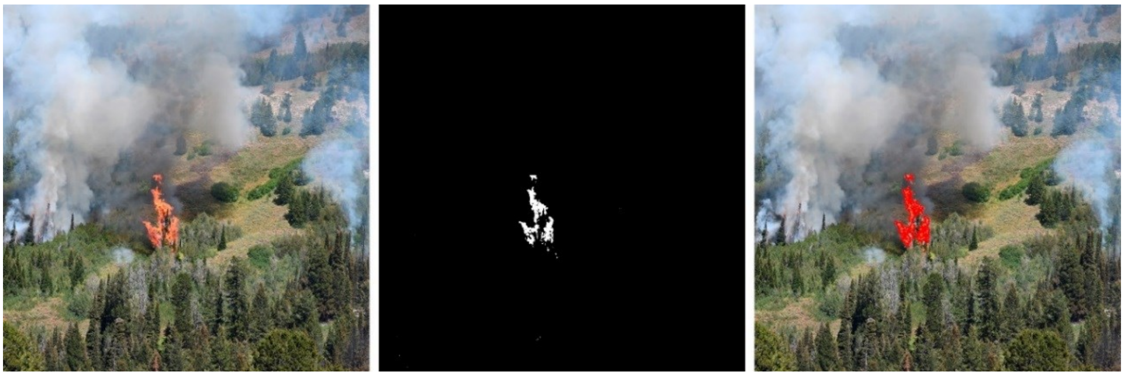


Figure 7. Fuzzy surface

All images are taken from real fires captured from the air. RGB images are converted to HSI color space, then the S and I values for each pixel are calculated and provided as input to the fuzzy system. In the output, fire pixels appear as shades of red, and smoke pixels appear as shades of white. Thresholds for fire are 0.75 and 0.59 for smoke, respectively. Thresholds are set to achieve the best balance between accurate fire identification and false detections. This system is shown to be capable of simultaneously effectively detecting fire and smoke. Example results of the proposed algorithm are shown in Figure 8 (a-d).

a) fire segmentation example

b) smoke segmentation example



c) fire segmentation example

d) both fire and smoke segmentation example

Figure 8. Results of fire and smoke detection: original images (left), fuzzy segmentation (middle), and final result (right)

Experimental results have shown that the method allows achieving up to 95 % fire front recognition accuracy, but requires a good camera calibration. The results show that the proposed method works very well if the color characteristics are in the given range. Changing threshold values speeds up computing, but reduces accuracy. In future work, we plan to use additional parameters such as shape, movement, etc. in addition to color information, which will increase the efficiency of the algorithm.

Conclusions. This article proposes the use of fuzzy logic-based image processing to identify fire and smoke in wildfire images. The technique, built on the method of simultaneous identification of fire and the possibility of detecting smoke, significantly expands the capabilities of earlier algorithms. To reduce complexity, only color information is used. The proposed methodology is designed to be applied in the early stages of a forest fire when the fire has just started and the amount of smoke is low. The method provides sufficient performance to meet the efficiency requirements.

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