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Enhancing Fire Detection Technology: A UV-Based System Utilizing Fourier Spectrum Analysis for Reliable and Accurate Fire Detection

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Abstract: This study proposes a low-cost and reliable smart fire alarm system that utilizes ultraviolet (UV) detection technology with an aspherical lens to detect fires emitting photons in the 185–260 nm range. The system integrates the aspherical lens with an accelerator and a digital compass to determine the fire source's direction, allowing for safe evacuation and effective firefighting. Artificial intelligence is employed to reduce false alarms and achieve a low false alarm rate. The system's wide detection range and direction verification make it an effective fire detection solution. Upon detecting a fire, the system sends a warning signal via Wi-Fi or smartphone to the user. The proposed system's advantages include early warning, a low false alarm rate, and detection of a wide range of fires. Experimental results validate the system's design and demonstrate high accuracy, reliability, and practicality, making it a valuable addition to fire management and prevention. The proposed system utilizes a parabolic mirror to collect UV radiation into the detector and a simple classification model that uses Fourier transform algorithm to reduce false alarms. The results showed accuracies of approximately 95.45% and 93.65% for the flame and UVB lamp, respectively. The system demonstrated its effectiveness in detecting flames in the range of up to 50 m, making it suitable for various applications, including small and medium-sized buildings, homes, and vehicles.

Keywords: smart fire alarm system; ultraviolet detection technology; direction detection; low false alarm rate; fourier transform algorithm

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1. Introduction

Fire alarm systems are essential safety requirements in various settings, such as factories, companies, seaports, and houses. The need for early fire warning has spurred the development of smart and sensitive alert systems. Currently, commercial flame detectors in use operate based on either heat measurement or smoke detection principles. Smoke sensors available in the market operate within a thermal band of −10 °C to 50 °C and have a slow response time of 10–30 s [1–4]. These sensors are triggered when the smoke's dimming falls within the range of 5%–20%. Heat sensors use heat resistance to obtain accurate heat measurements, but their response speed is low, ranging from 15 to 90 s. Additionally, they require contact with the heat source, and their operating temperature is between −10 °C and 50 °C. Although smoke and thermal sensors are widely used and low-cost, their response speed, sensitivity, and working range are limited. Smoke sensors only detect smoke and not the fire source itself, which can be dangerous when the fire grows on a large scale. These sensors work best in closed spaces [1–4]. However, in open spaces, they may fail to detect fires accurately due to air currents and other factors. As a result, new fire detection systems that utilize novel techniques and technologies, such as ultraviolet detection and Fourier spectrum analysis, have been developed to address these limitations and enhance fire safety.

Fire alarm systems are essential in various settings, such as factories, warehouses, seaports, and homes. The development of smart and sensitive alert systems that can detect fires at an early stage is crucial for the safety of people and property. While conventional fire detection systems use heat or smoke sensors, recent advancements have led to the development of more sophisticated systems that employ different techniques, such as image processing and infrared/ultraviolet sensors. Infrared (IR) sensors are commonly used in fire detection systems and can detect heat sources with temperatures of 200 °C to 300 °C above the base temperature. However, the limitation of IR and IR/UV sensors is that they may not be able to detect fires with low temperatures, and their sensitivity is affected by noise from heat sources in the ambient environment and solar radiation [5–8]. Despite these limitations, these sensors are widely used in many fire alarm systems due to their cost-effectiveness and relative reliability. Recently, fire detection systems based on image processing techniques have gained traction [9–12]. These systems use cameras and sophisticated algorithms to analyze the captured images and identify fires. For instance, an integrated long-wave IR and mid-wave IR bolometer camera with a dual-band filter has been reported to detect flames from 30 to 200 feet outdoors, depending on the fire source. However, this detector cannot detect flames in all directions [13–16]. Another fire monitoring system uses both IR sensing and color videos and can detect the burning of smokeless liquids, gas fires, and fires of materials that contain carbon and produce a lot of smoke. The cameras used to localize the fire can be integrated into the security system, but this device is difficult to install in hidden areas and is rather short-lived [17–23]. In summary, while traditional fire detection systems using heat and smoke sensors have their limitations, recent advancements in image processing and infrared/ultraviolet sensors have shown promising results in early fire detection. However, each system has its advantages and disadvantages, and the selection of a fire alarm system depends on various factors such as the size of the building, the type of materials stored, and the location of the fire detection system.

Uncooled IR detectors have become a popular choice for industrial applications due to their ability to detect gases of interest, whose strongest bands are found in the 1–5 micron range. Compared to other commercial IR sensors, uncooled IR detectors offer better response time, making them highly sensitive and able to provide both spatial and temporal information. However, their area of detection is often narrow, which can limit their effectiveness [24,25]. In recent years, Internet of Things (IoT) sensors have played a critical role in primary flame detection. A camera-based system that utilizes multiband IR imagery and thermal analysis has been developed for wildfire detection. This system incorporates LoRa-based wireless communication for long-distance monitoring. Researchers have used the Dempster-Shafer theory and Linear Discriminant Analysis for data analysis and detection of false positives. Despite its effectiveness, the mathematical prediction model for this system is quite complicated and can be difficult to compute [26].

In recent years, fire detection technology has advanced rapidly, with the development of new systems that offer improved accuracy and speed in fire detection. One such system is a Low-Earth Orbit system that utilizes long- and shortwave IR sensors to detect and measure actively burning fires on the Earth's surface [27]. This system is particularly useful for monitoring large areas, such as forests, where traditional ground-based fire detection systems may not be sufficient. In addition to satellite-based systems, smart fire warning and alarm systems are also becoming more sophisticated. These systems typically use multiple sensors, such as flame detectors, humidity, heat, and smoke sensors, among others, to detect fires. To process the data from these sensors and generate a fire alert, Adaptive Neuro-Fuzzy Inference System is commonly employed [28,29]. Despite the benefits of multi-sensor and IoT-based fire detection systems, these technologies also have some drawbacks. For example, they may suffer from slow response times, low sensitivity, high cost, and high system complexity, which can make them difficult to install and maintain.

This paper introduces a new approach to fire detection and warning systems that offers a smart, compact, and cost-effective solution. The system incorporates a UV detector that operates in the range of 185–260 nm to detect the signal from the fire source, making it suitable for identifying the burning of different materials at various rates. To eliminate background noise, the signal processing circuits have been designed to cancel out any sporadic noise that may arise due to the background. The system also determines the direction of the fire source, allowing for more precise and efficient fire extinguishing. The alarm signal can be generated in a high-frequency pulse shape (100 Hz) and transmitted to a computer via Wi-Fi or sent to the user's smartphone. Experimental results demonstrate that the system can detect a fire source within a range of 50 m. Furthermore, an artificial intelligence (AI) system has been developed to prevent false alarms. The proposed system is well-suited for use in warehouses, seaports, and factories, and can be integrated into a monitoring network. The innovative approach presented in this paper offers a new, effective solution for fire detection and warning systems that can enhance safety and reduce property damage.

2. System Design

The fire detection system proposed in Figure 1 comprises several essential components. A UV detector, specifically the Hamamatsu UVtron R12257 (Hamamatsu Photonics, Shizuoka, Japan), is utilized in the system. This detector demonstrates high sensitivity and boasts a rapid response time of just a few milliseconds, enabling it to effectively detect UV radiation emitted by flames. The sensor operates within a selective spectral range of 185–280 nm, eliminating the need for optical filters to block out visible light. Its output consists of a series of pulses that persist for a duration sufficient to identify genuine flames. While this pulse-based output helps filter out background noise within the sensor's field of view, it is important to consider potential interference sources. Heat-emitting devices, such as automobiles or processing machines, may emit minimal amounts of UV radiation, which can serve as a possible source of interference. The UV radiation is focused onto the sensor using a parabolic mirror, the Sigmakoki Inc. (Tokyo, Japan) TCPA-105C-15-SH18, mounted on a precise rotation stage, which scans the entire monitoring area. The scanning direction of the mirror is determined by a digital compass and an accelerometer that are integrated into the stage, and the output signal from the sensor and the position of the mirror are used to determine the fire's location. To eliminate sporadic noise that may occur due to the background, the signal processing circuits have been designed to cancel out any such noise. Additionally, the system determines the direction of the fire source, allowing for more accurate and effective fire extinguishing. The alarm signal generated by the system can be transferred to a computer via Wi-Fi or sent to the user's smartphone in a high-frequency pulse shape (100 Hz).

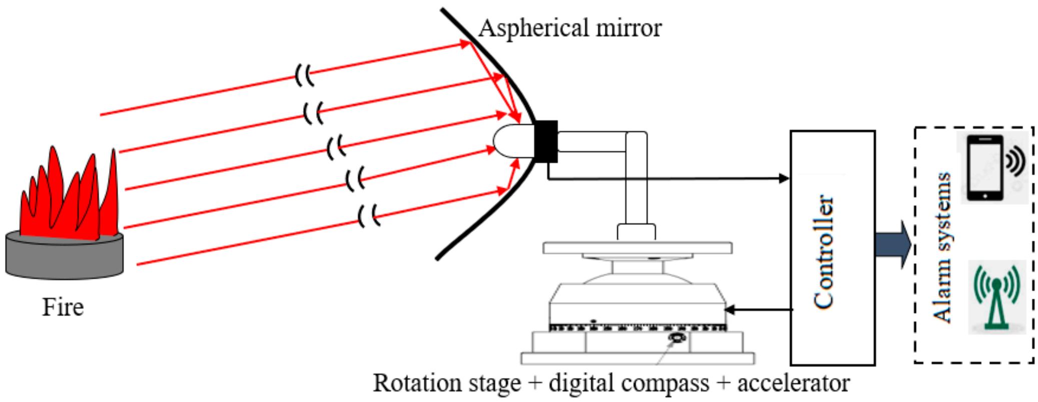


Figure 1. Fire detection system.

In the case of a fire, the proposed fire detection system immediately generates a warning signal. This signal can be transmitted to an alarm system, which can be accessed on a smartphone or via Wi-Fi. The warning signal can alert the user to the presence of a fire, allowing them to take immediate action. Additionally, the system's operation can be monitored in real-time from a monitoring center. This monitoring center can be set up to monitor the system's performance and status, ensuring that the system is functioning properly and that any problems or malfunctions are quickly detected and resolved. The monitoring center can also provide valuable data and information about the fire, such as its location, intensity, and spread, which can be used to help first responders and firefighters effectively combat the blaze. Furthermore, the real-time monitoring capability of the system can help prevent false alarms and provide a high level of accuracy in detecting fires, thus minimizing the risk of property damage and ensuring the safety of occupants.

The control circuit for the fire detection system is an essential component of the system, and it plays a significant role in ensuring the system's accuracy and effectiveness. As shown in Figure 2, the circuit consists of several key components that work together to provide a reliable and efficient solution for detecting fires. The UVtron control unit supplies high voltage to the sensor and produces short pulses warning signals when the sensor is exposed to UV radiation. The output pulses, which last for 10 ms, are sent to a microprocessor (Arduino Uno R3), which is responsible for processing the signals and controlling the system's operation.

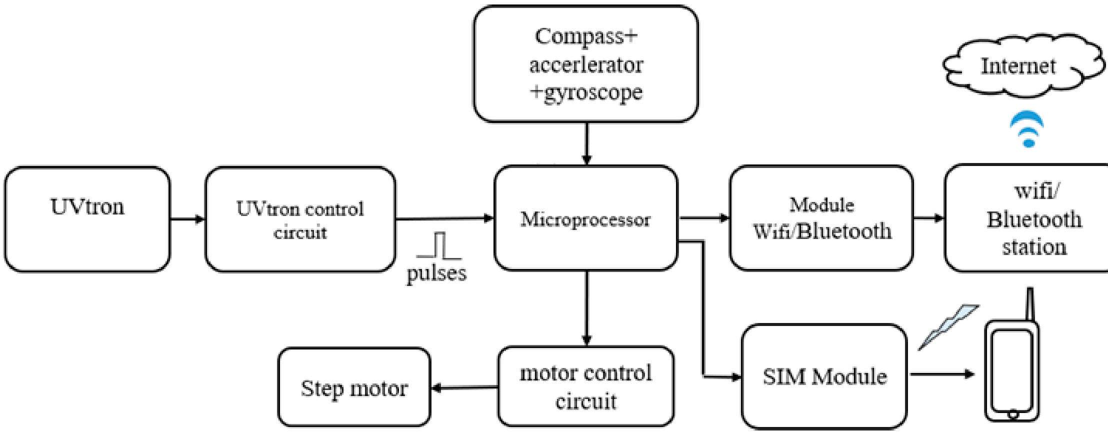


Figure 2. Control circuit for the fire detection system.

Since the effective area of the UV sensor is small, and the sensing field is limited to an angle of 70°–120°, photons radiate from various directions, making it challenging for them to hit the sensor's focal point. To overcome this issue, a stepper motor (MSK 4240-400) is attached to the microprocessor, which rotates the parabolic mirror, enhancing the system's sensitivity and effective working range. The direction of the mirror is determined using digital compass, gyroscope, and accelerometer signals, which allow for accurate detection and localization of the fire.

The microcontroller is linked to a SIM block (SIM900A Mlab, Hanoi, Vietnam) to send alarms to a mobile phone that is already installed. Additionally, the microcontroller has a Wi-Fi module (RF 433 MHz Transmitter/Receiver) that enables it to communicate with a smartphone through the internet. This allows for remote monitoring of the system's operation, providing real-time data on the fire's location and intensity. The integration of these components into a single circuit provides a compact and cost-effective solution for fire detection, making it suitable for use in various settings, such as warehouses, factories, and seaports.

3. Experiment

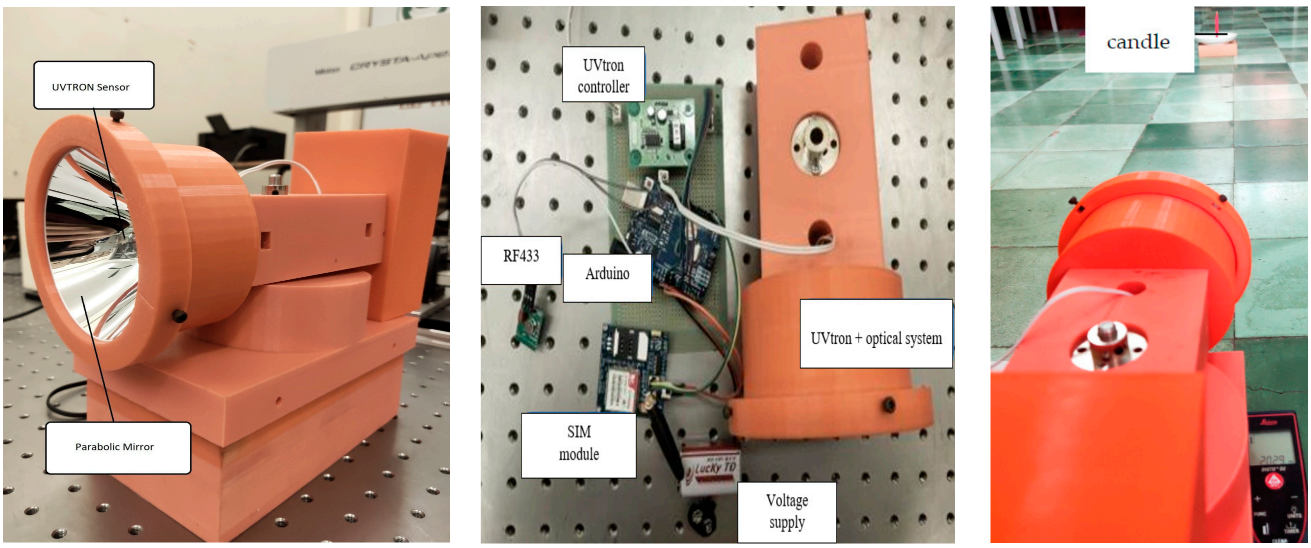
The fire detection system's effectiveness in detecting fires was evaluated through comprehensive testing under varying experimental conditions, considering both short-range and long-range capabilities. Table 1 provides an overview of the experimental conditions, while Figure 3 illustrates the system employed for the fire detection test. The experiments were conducted during daylight hours, acknowledging that environmental factors can influence the test results. Specifically, the presence of sunlight could emit UV radiation within the sensor's targeted range of 185–280 nm. To mitigate this, our fire detection system implementation ensures that the sensor is not directly exposed to sunlight. In practical applications, the device is installed overhead, facing downwards. For assessing the system's short-range capabilities, a candle was utilized as the test fire, positioned at distances ranging from 1 to 10 m. The distance between the fire sensor and the candle was accurately measured using a laser distance meter (Leica Disto D2, Leica Geosystems AG, St. Gallen, Switzerland), which provides a measurement range of up to 100 m. To identify the fire's location, the fire detection system was rotated around the test area, comparing the density of generated pulses. The outcomes of the experiment, specifically the results obtained at the fire's location, are presented in Figure 4.

To evaluate the system's long-range detection capability, a fire with a size of 300 mm × 300 mm was used as the test object. The experimental setup and results for the long-range test are shown in Figure 5, which includes the experiment setup in (a) and the stable warning signal in (b). The experiment demonstrated that the system can detect fires at distances of up to 50 m. It is worth noting that the warning signal remained stable throughout the long-range detection experiment, which demonstrates the system's ability to effectively detect fires even at extended distances.

The experimental results indicate that the proposed fire detection system is highly effective in detecting fires, both at short and long distances. The system's use of a UV detector with a rapid response time and the ability to cancel out background noise, coupled with the rotation of the parabolic mirror to enhance its sensitivity, enables it to accurately detect fires and provide timely warnings to prevent property damage and protect lives. The system's ability to send warning signals to a smartphone or via Wi-Fi and to be monitored in real-time from a monitoring center further enhances its capabilities and makes it suitable for use in warehouses, seaports, and factories.

Table 1. Condition of the fire detection experiment.

Measurement target size	Short range: 5 mm × 10 mm Long range: 300 mm × 300 mm
Testing distance	Short range: 1.5, 3.0, 5.0, 10.0 m Long range: 50 m
Detected wavelength range	185–280 nm
Power supply	12 V
Current supply	2 mA



(a) (b) (c)

Figure 3. Experimental fire detection system and setup used to verify its measurement range and sensitivity: (**a**,**b**) experimental system in detail; (**c**) test of the fire detection experiment using a candle.

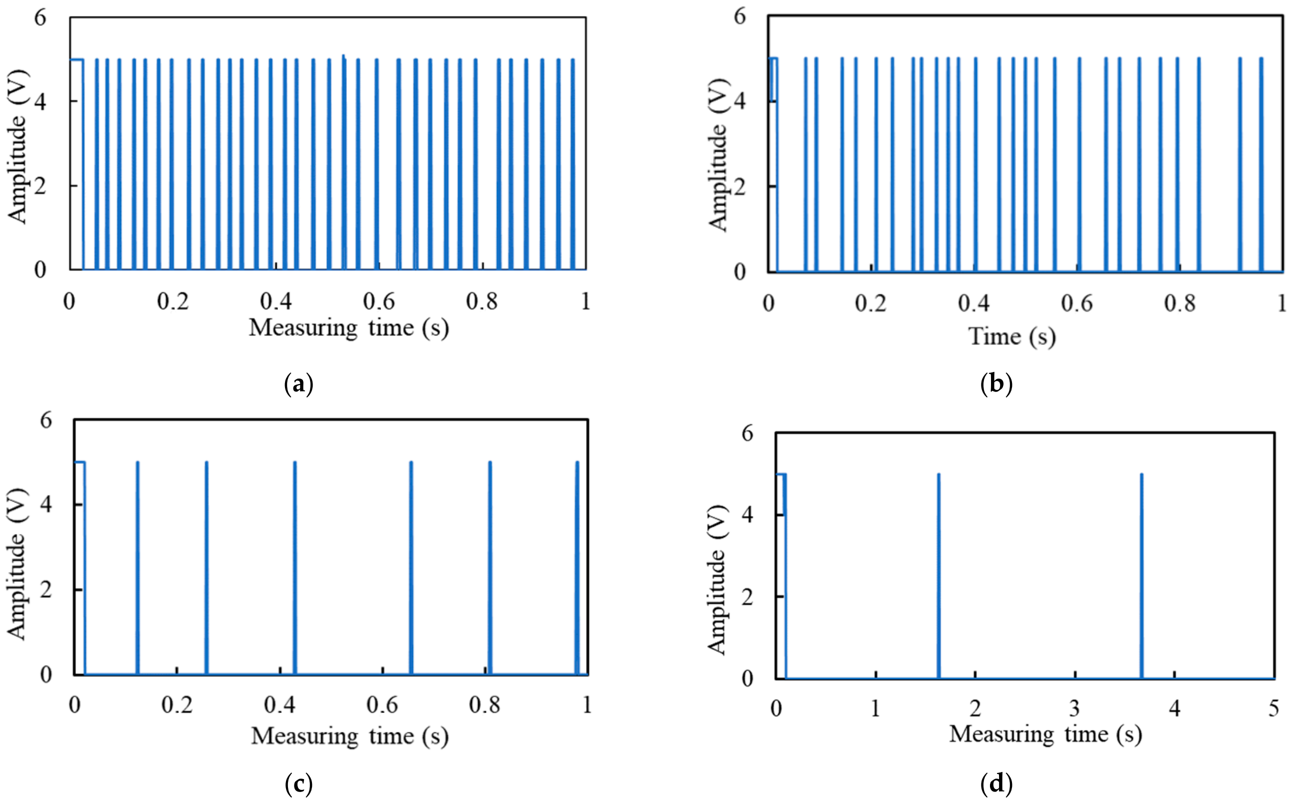
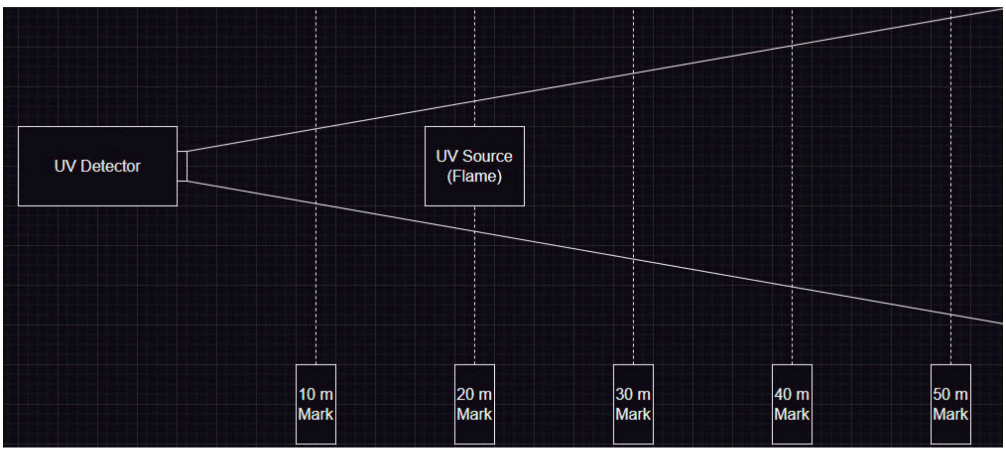


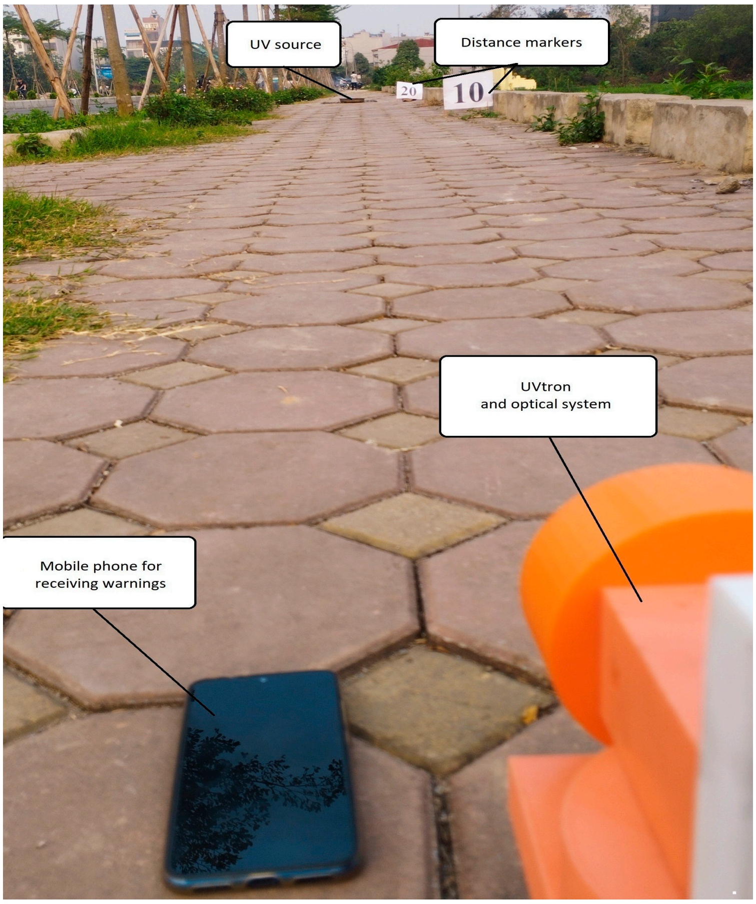
Figure 4. Experimental results for short-range detection: (**a**) 1.5 m; (**b**) 3 m; (**c**) 5 m; (**d**) 10 m.

The experimental results indicate that the fire detection system is capable of accurately detecting the presence of a fire source within a maximum distance of 50 m. The system's detection capability is optimized for specific dimensions of 300 mm × 300 mm, ensuring reliable and precise identification of fire sources within this defined area. The reliable and accurate detection of fires is critical for ensuring safety in various industries, including chemical, petroleum, and electrical power. False alarms can lead to costly disruptions, reduce efficiency, and cause unnecessary evacuations. Therefore, it is essential to develop techniques that can accurately distinguish between UV radiation emitted from flames and other sources.

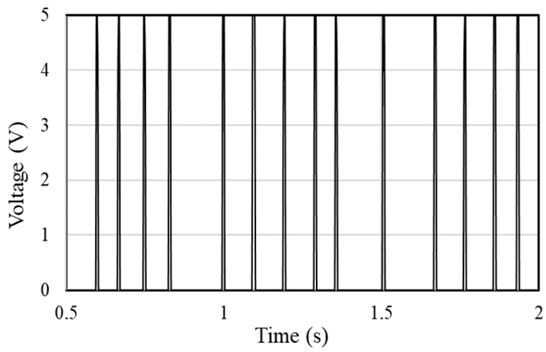


(**a**)

Figure 5. *Cont.*



(b)



(c)

Figure 5. Diagram for experimental setup for fire detection at various distances (**a**); real look of experimental setup (**b**); illustration of output signal (**c**).

One approach to minimizing false alarms is to exploit the chaotic nature of radiation from an uncontrolled flame. Unlike other sources such as UV lamps, heaters, and sunlight, combustion involves nonlinear instabilities that result in chaotic emission. This characteristic can be used to distinguish flame signals from other signals that tend to be regular. This study used the Naïve Bayes classification algorithm with the signal spectral characteristics in the frequency domain to distinguish between signals from a flame and a controlled UV source (UVB lamp). The proposed approach was evaluated using a dataset obtained from a fire detection system equipped with a UV detector, and the results, presented in Figure 6, demonstrate the algorithm's robust accuracy and efficiency. These findings provide strong evidence for the potential of this technique in effectively reducing false alarms in fire detection systems.

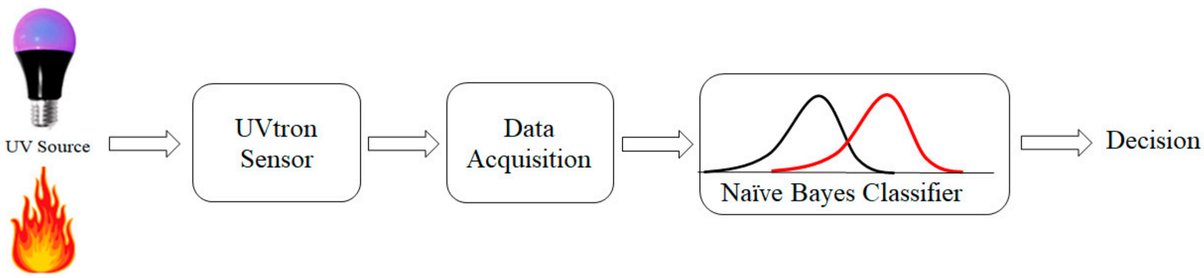
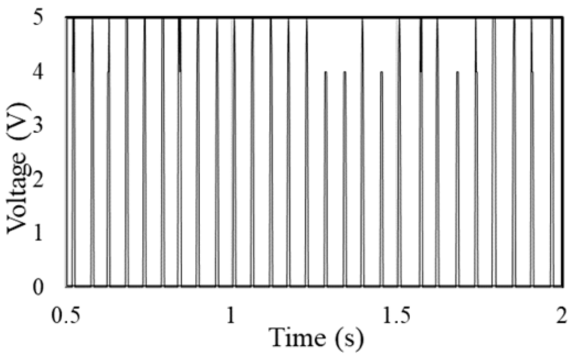
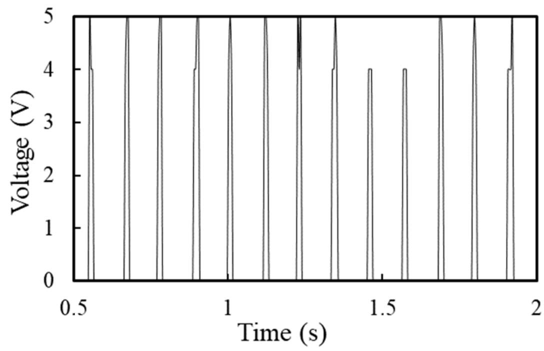


Figure 6. Naïve Bayes classifier model applied to the UVtron fire detection system. Distributions of two classes are represented by black and red line.

The study aimed to distinguish signals from a flame and a controlled UV source using Fourier spectrum analysis as the classification algorithm. The UVB lamp was modified by limiting the surface area of the radiation source with a pinhole of 10 mm × 10 mm in front of it. The resulting signal data obtained from the UVtron sensor appeared as a time series consisting of pulses lasting 10 ms, as shown in Figure 7. The sensor's output signal in response to the UV source consists of a series of fixed-width (10 ms) pulses, exhibiting varying amplitudes (between 4 VDC and 5 VDC) due to conditioning circuit operations. The pulse signals depicted in Figures 6 and 7 represent random selections from the overall output signal obtained during the measurements. The signal pulses from the flame were found to be more discrete than those from the UVB lamp, indicating that the sensor responds to the flame in a more chaotic manner. Fourier spectrum analysis was applied to obtain information on the signal's amplitude at different frequencies, where larger amplitude at any frequency indicated more signal pulses at that frequency and vice versa. Therefore, the Fourier spectrum analysis result for the signal output over a specific period of time was used as the data feature for classification in this study. It is important to note that in the case of the flame, the pulse duration steps for each distance were not uniform at different moments in time, and the time-step magnitude distribution was also non-uniform. Thus, Fourier spectrum analysis was chosen as a robust algorithm that could handle such non-uniformity in the pulse duration and magnitude distribution.



(**a**)



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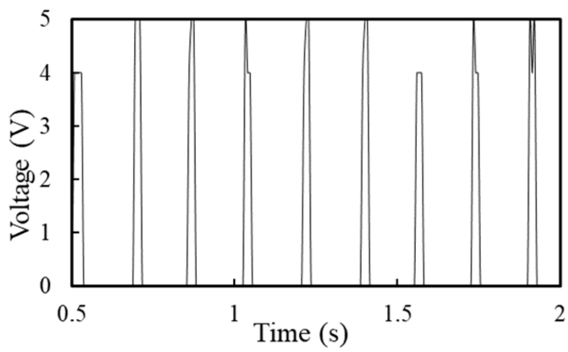
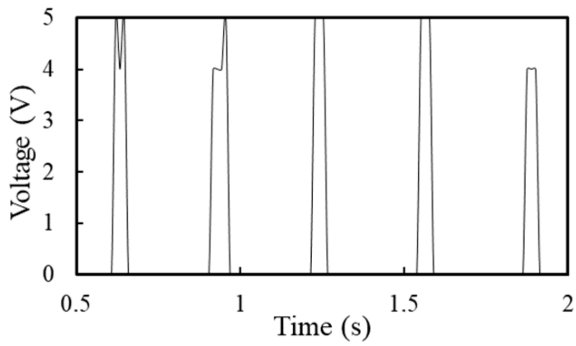


(**c**)



(**d**)

Figure 7. Output signals of the sensor responding to the UV lamp placed at different distances. (**a**) 1.5 m; (**b**) 3 m; (**c**) 5 m; (**d**) 10 m.

The signal pulses from the flame (Figure 7) were found to be more discrete than those from the UVB lamp, indicating that the sensor responds to the flame in a more chaotic manner. Fourier spectrum analysis was applied to obtain information on the signal's amplitude at different frequencies, where a larger the amplitude at any frequency indicating more signal pulses at that frequency, and vice versa. The data feature for classification was therefore the Fourier spectrum analysis result for the signal output over a specific period of time.

To extract the features, the time series of the output signal was divided into windows of duration 250 ms, corresponding to N = 100 samples each, and denoted as $\boldsymbol{x} = [x_1, x_2, \ldots, x_N]$. Fast Fourier Transform was then applied to each window, resulting in a vector of power of spectrum $\boldsymbol{X} = \left[X_1, X_2, \ldots, X_{\frac{N}{2}}\right]$ with a dimension of N/2 = 50. Here, each X_k represents the spectrum power at a frequency of $k \times F_1$, with F_1 = 4 Hz as the fundamental frequency. Figure 8 provides examples of the normalized Fourier spectrum analysis of the signals obtained from the flame and UVB lamp.

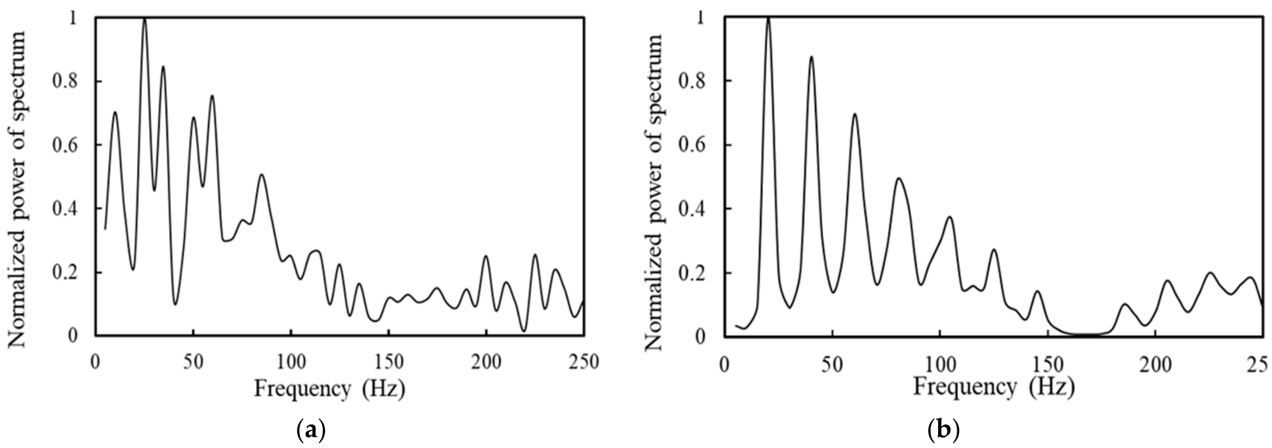


Figure 8. Normalized Fourier spectrum analysis results for the output signals of a flame (**a**) and UV lamp (**b**).

The Fourier spectrum analysis results of the flame, as observed in this study, were observed to exhibit significant variability over time, indicating that the signal feature space may be difficult to model using standard techniques. To address this challenge, constructing distributions for the vector of spectrum power X was considered as a viable solution to the classification problem. Specifically, the Fourier spectrum amplitude values for each frequency over time were treated as random variables, and the joint probability distribution for these values was constructed. In this case, the input features were the Fourier spectrum amplitude values for each frequency, and the classification models were used to classify new signals as either coming from the flame or the UVB lamp.

Due to the fact that the data that needs to be classified currently has exactly two classes, it is implied that the classification can be done with the Support Vector Machine (SVM) method, which is suitable for edge devices [12]. The advantages of this method can be listed as follows: it is effective in high-dimensional spaces, even in the cases where number of dimensions is greater than the number of samples; it is memory efficient due to the fact that it uses a subset of training points in the decision function; it offers flexibility in various kernel selection. In this work, the idea comes with using SVM for binary classification in which the data is labeled with $y = 1$ for the flame and $y = -1$ for the UBV lamp. The aim of this method is to find the function of a hyperplane over the feature vector X, which is the vector of spectrum power in this work:

$$f(X) = X^T \beta + b \quad (1)$$

Hence, it is necessary to specify the parameters β, b that must meet certain criteria. In practical, our data appears to not allow for a separating hyperplane. Therefore, the objective function to estimate β, b in this work presents the L^1-norm problem, which is constructed by adding slack variables ξ_j and a penalty parameter C, as follows:

$$\min_{\beta,b,\xi} \left(\frac{1}{2}\beta^T \beta + C\sum_j \xi_j^1 \right) \quad (2)$$

subjected to the constraints:

$$y_j f\left(X_j\right) \geq 1 - \xi_j \text{ and } \xi_j \geq 0 \forall j \quad (3)$$

On the other hand, it was possible to capture the inherent variability of the flame signal over time and encode this information into a probabilistic model. This approach allowed for the development of a Naïve Bayes model, which is a type of probabilistic classifier that assumes the independence of the input features. Overall, this approach proved to be effective at accurately distinguishing between these two types of signals and may be useful in other applications where signal variability poses a challenge to traditional classification techniques.

The Naïve Bayes classifier is typically used when predictors are independent of each other within each class. However, it has been shown to perform well in practice even when the independence assumption is not valid. Specifically, the Naïve Bayes model estimated the probability density of predictor X (the vector of spectrum power) given class y-(flame or UVB lamp), denoted by $P(\boldsymbol{X} \mid y)$. Therefore, the Naïve Bayes model resulted in parameter vectors $\boldsymbol{\mu}$, $\boldsymbol{\sigma}$, $\boldsymbol{\mu}'$, $\boldsymbol{\sigma}'$ with dimensions of 50 for the following probability densities:

$$P(\boldsymbol{X}|y = flame) = \prod_{k=1}^{50} \frac{1}{\sigma_i \sqrt{2\pi}} \times \exp\left(-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}\right) \quad (4)$$

$$P(\boldsymbol{X} \mid y = UV\ lamp) = \prod_{k=1}^{50} \frac{1}{\sigma'_i \sqrt{2\pi}} \times \exp\left(-\frac{(x_i - \mu'_i)^2}{2\sigma'^2_i}\right) \quad (5)$$

The present study utilized the parameter vectors obtained from assuming a Gaussian distribution for $P(\boldsymbol{X} \mid y)$ to classify signals into either flame or UVB lamp classes based on the probability of the spectrum power vector X belonging to each class, utilizing Bayes' theorem. The Naïve Bayes model was found to be an effective approach for classifying signals based on their Fourier spectrum analysis results.

The results of this study demonstrate the potential of using the SVM classifier and Naïve Bayes classifier based on Fourier spectrum analysis to distinguish between signals from a flame and a UVB lamp. The classifiers were trained using 1000 samples of both the flame and UVB lamp and were evaluated with 500 samples of each. By using the SVM classifier with the penalty parameter C = 10, the accuracies obtained in the testing phase were 95.15% and 91.25% for flame and UVB lamp classification, respectively. Meanwhile, the results of performing the Naïve Bayes classifier were 95.45% and 93.65% for flame and UVB lamp classification, respectively. These findings suggest that the SVM classifier and Naïve Bayes classifier are reliable methods for accurately differentiating between signals from a flame and a UVB lamp based on their Fourier spectrum analysis results.

The high accuracies achieved in this study offer a promising solution to the problem of false alarms in fire detection systems. By minimizing false alarms, the proposed system has the potential to save lives and minimize property damage. Additionally, the use of Fourier spectrum analysis to extract features of the flame and UVB lamp signals offers a robust and effective method for fire detection.

Future research could further investigate the effectiveness of this approach in more complex environments, such as those with multiple sources of UV radiation or in the presence of smoke. Additionally, exploring the potential for integrating this system with other fire detection methods could lead to even greater accuracy and reliability in fire detection.

4. Conclusions

In this study, we presented a low-cost and efficient fire detection system that utilized UV radiation detection and Fourier spectrum analysis. By utilizing a parabolic mirror and digital sensors, we were able to detect the position of the fire accurately. Furthermore, the proposed classification models, based on the Fourier transform algorithm, successfully extracted features of a fire and a UV source, which enabled us to minimize the occurrence of false alarms. The experimental results showed that the proposed system achieved high accuracies of 95.15% and 91.25% using the SVM classifier, and approximately 95.45% and 93.65% using the Naïve Bayes classifier for the flame and UVB lamp, respectively.

Our proposed system offers several benefits compared to existing fire detection systems. It is cost-effective, making it a viable option for small and medium-sized buildings, homes, and vehicles. Moreover, the system's simple design and high accuracy make it attractive for use in areas where expensive systems are not feasible. Our system has been shown to be effective in detecting flames up to 50 m away, making it suitable for a wide range of applications.

In conclusion, the proposed system has demonstrated the effectiveness of using UV radiation detection and Fourier spectrum analysis as an efficient method for fire detection. Future studies could explore ways to improve the system's performance in challenging environments and investigate its potential for integration with other fire detection systems. This study provides valuable insights into the development of low-cost and efficient fire detection systems that can contribute to the safety of individuals and properties.

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