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A Data Fusion-Based Fire Detection System

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SUMMARY To prevent constraints or defects of a single sensor from malfunctions, this paper proposes a fire detection system based on the Dempster-Shafer theory with multi-sensor technology. The proposed system operates in three stages: measurement, data reception and alarm activation, where an Arduino is tasked with measuring and interpreting the readings from three types of sensors. Sensors under consideration involve smoke, light and temperature detection. All the measured data are wirelessly transmitted to the backend Raspberry Pi for subsequent processing. Within the system, the Raspberry Pi is used to determine the probability of fire events using the Dempster-Shafer theory. We investigate moderate settings of the conflict coefficient and how it plays an essential role in ensuring the plausibility of the system's deduced results. Furthermore, a MySQL database with a web server is deployed on the Raspberry Pi for backlog and data analysis purposes. In addition, the system provides three notification services, including web browsing, smartphone APP, and short message service. For validation, we collected the statistics from field tests conducted in a controllable and safe environment by emulating fire events happening during both daytime and nighttime. Each experiment undergoes the No-fire, On-fire and Post-fire phases. Experimental results show an accuracy of up to 98% in both the No-fire and On-fire phases during the daytime and an accuracy of 97% during the nighttime under reasonable conditions. When we take the three phases into account, the accuracy in the daytime and nighttime increase to 97% and 89%, respectively. Field tests validate the efficiency and accuracy of the proposed system.

key words: *multi-sensor, short message service, data fusion, Dempster-Shafer theory*

1. Introduction

As fire often brings about danger, advance warning of fire events is a necessity. To achieve this, fire detection is an essential requirement. Traditionally, a single sensor is likely of limited use and easily affected by surrounding environments. Accordingly, false alarms or system malfunctions may arise. As a remedy, this paper presents a fire detection system with multi-sensor technology that applies the Dempster-Shafer theory to improve overall accuracy. The Dempster-Shafer theory is well known for reasoning with uncertainty, dealing with events of imprecise probabilities, and producing correct and intuitive results by fusing constraints from multiple information sources. In addition, the Dempster-Shafer theory does not require complicated computations, which increases the ease of implementation in programming. Therefore, we used the Dempster-Shafer theory for subsequent development.

In previous literature, there has been a great deal of research on multi-sensor technology with data fusion. In particular, Wang *et al.* [1] proposed a framework of a fire hazard ranking distribution system based on multi-sensor technology in line with the next generation of fire detection technology that supports fire emergency management and rescue relief. The system refers to a network of geographically dispersed nodes that collect the sensor data for monitoring purposes. Collected data for the purpose of detecting fire events and fire positions from different sources are delivered to a cloud. Although effective, the backend cloud in the framework operates based on fuzzy rules, at the expense of computational cost. Computational complexity arises when the system requires evaluating conjunctions of antecedents of all applicable fuzzy rules, whose base can grow exponentially with the number of fuzzy sets and linguistic values. Still, our scheme is of avail to the framework in that involved deduction can be bypassed with a different approach, as shall be shown below. After reviewing the current status of a fire detecting system, Liu *et al.* [2] concluded that the latest technologies such as multi-function sensors, wireless sensors and real-time control via the internet will improve safety and reduce false alarms, improve response time so that the monitoring and controlling of building service systems can increase in efficiency, reduce costs for building management operations, more efficiently discriminate between fire and safe conditions, and increase the time available for property and life protection. Ding *et al.* [3] proposed a system to avoid the failure of monitoring data with multi-sensors technology using the Dempster-Shafer theory to address conflicting evidence to improve the accuracy of the whole system. They used the Dempster-Shafer theory to fuse data from several sensors for each experiment to create their evidence. Lastly, they combined this evidence to arrive at new evidence using the Dempster-Shafer theory to calculate the probability of fire, no-fire and uncertainty. Shinghal [4] developed a multi-sensor system for agricultural fire detection to improve the efficiency of the traditional system only relying on the human observers and mechanisms. The system proposed to use multi-sensor technology, wireless communication and miniature autonomous power supplies. The proposed system collects data from sensors using a fusion algorithm to increase the reliability, reduce the prob-

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ability of false alarms, and detect network data utilization to timely alert farmers. Asif *et al.* [5] provided a review of existing fire-detector types available. He also designed a low-cost, portable, and reliable microcontroller based automated fire alarm system. There are 6 data lines to receive sensors' measured data from gas/smoke, temperature and flame sensors. The threshold value of the temperature is set to 50°C and system operates on the 850/1900 MHz and 900/1900 MHz frequency bands. There are ten tests on inputs of different input data combinations, and the average response time is measured to be between 7 and 10 seconds.

Sekks et *al.* [6] proposed a fire detection approach based on multi-level scheme data fusion using Dempster-Shafer theory with wireless sensor networks technology. In this approach, the first level is designed to get raw data from sensors over a data fusion technique to fuse data and assign a probability of fire occurrence to each sensor. In the second level, it combines the probability of fire from the first level by Dempster-Shafer theory with a vision sensor added. Two layers of the fusion technique were adopted to improve the reliability of the fire detecting system. Vakulya and Simon [7] proposed a sensor network-based distributed security framework, which can distribute alarm messages in the whole network with low latency and high power efficiency that are the merits of TDMA (Time Division Multiple Access). In the proposed system, the operation is completely distributed, and has the potential to tolerate even a single point failure. The sensors construct a wireless network and each node acts autonomously on its own action. The network propagates not only alert messages but status information as well. Su *et al.* [8] proposed a security system to detect fire sources and find the safe path to evacuate using Bayesian probability method to estimate the risk value of cross points for multiple fire sources, then looked for the shortest deviating path with A* searching path. Chia *et al.* [9] proposed a robot fire detection system with one team for flame sensor and another team for gas leakage sensor using Dempster-Shafer theory to address the conflict evidence to improve the accuracy of fire detection. After integrating detection from sensors, the result is concluded from the value that holds that fire is detected if the fire detection value is higher than the threshold value; otherwise, it is considered safe. Guo *et al.* [10] proposed a security system to detect a fire event and program the evacuation path using risk value calculated by a Gaussian mass function method and A* searching algorithm to find the shortest path to evacuate.

From the existing systems designed, multi-sensors and network, especially wireless RF transmission technique, are the most common [1]–[4], [6]–[8], [10]. With regard to data fusion to integrate and analyze the data from the multi-sensors, we find many systems using the Fuzzy theory [6], the Bayesian estimation method [8], the Dempster-Shafer theory [3], [6], [9], the Gaussian probability algorithm [10], the Neuro Network and so on. However, aforementioned fire detection systems with a single sensor operate using malfunction-inclusive technology. A malfunction may interfere with the decision making significantly, and thus a false alarm effect remains likely. Additionally, we stress that our proposed Dempster-Shafer theory can improve the accuracy of all systems since our design is used to rule out conflict evidence in multi-sensor frameworks that these previous technologies may experience, making decisions less susceptible to multi-sensor variations. However, this study proposes the Dempster-Shafer theory for improving the accuracy while maintaining sufficient performance.

In contrast to this work, our system takes the K conflict parameter into direct account, where a decision can be made in reflection of realistic multi-sensor detecting dynamics. In comparison with variants of sensors, the Dempster-Shafer theory reflects a significant performance improvement. However, the variation of dynamic multi-sensor remains an essential issue making the theory liable to unnecessary malfunctions at nontrivial costs. As a remedy, we adopt the Dempster-Shafer theory to address this issue.

Specifically for system implementation, one aspect may resort to using a single device such as the smoke sensor to detect fire events in a faster way. Though effective, such implementation acquires less environmental information, resulting in a higher likelihood of false alarms. Another approach adopts imaging techniques to locate flames. This approach is able to spot fire scenes precisely and remotely, yet at the expense of higher computational complexity. Other issues concern when and to whom to report when fires of different danger levels occur. As an affordable solution, we shall devise a system allowing for prescribed aspects to detect fire events timely in an efficient way. That is, we use inexpensive off-the-shelf sensor units, wireless modules, and a credit card-sized single board computer, namely, the Raspberry Pi featuring a system on a chip, to embody our mechanism. Our mechanism includes smoke, light and temperature sensors, with the measured data transmitted to the backend Raspberry Pi over Bluetooth for subsequent processing. The Raspberry Pi is core to deducing according to the Dempster-Shafer theory whether fire has happened. If so, our system activates notification services, including web browsing, smartphone APP, and short messages. This study distinguishes itself from previous work in the following aspects:

- This study identifies a fewer number of essential determinants that can be fused efficiently for accurate deductions. Accordingly, our detection process becomes simpler yet correctly fast responsive to emergency events, making our treatment applicable to real-time systems. In this study, we used 3 determinants, namely, temperature, smoke, and flame sensor whereas previous work on fire detection used several more evidences from sensors like humidity sensor, CO gas sensor and flame sensor for ultraviolet radiation detection or for image processing. As a result, we achieve a successful detection rate of over 90% within 2 to 4 minutes.

- Our approach is implemented over the platform of Raspberry Pi, Arduino, WiFi, Bluetooth modules and sensor units with necessary circuits. Further, we have also set up a web server plus a MySQL database co-located at the Raspberry Pi that keeps all the reported data from sensors and our deduction results in storage. An Android APP has been developed to connect over the Internet to the web server for remote access and for SMS notification in the fire event.
- To mimic real-life situations, we conducted experiments by setting up fire in a safe controllable environment, so as to observe how our implementation reacted in three different periods: no-fire, on-fire and post-fire. Moreover, field tests were carried out during daytime and nighttime, respectively, to see how our implementation performed in different settings. We believe that our experimental results are convincible enough to validate our development. To a great extent, our findings strengthen the usefulness of applying the D-S theory to multi-sensory fusion in pragmatic situations.

This article proposes a fire detecting system using multi-sensor technology based on the Dempster-Shafer theory to improve the reliability of the entire system by minimizing the interval of uncertainty probability. Fire requires complex processing. To characterize the potential complexity of fire detection system, only one or two dimensions of detection system such as time and space domains is usually proposed in a traditional system [1], [3]. Furthermore, we use the sensor type dimension to integrate the related information for analysis.

The rest of this work is organized as follows. The next section gives the system architecture, including system architecture and system operating flow. Section 3 describes the research method, including fundamental knowledge and functions explanation of the multi-data fusion algorithm used in this work. Field tests results and system performance evaluation are presented in Sect. 4. Lastly, Sect. 5 concludes this work.

2. System Architecture

The system frame consists of three stages: measurement, data reception and alarm activation, as shown in Fig. 1. In the measurement stage, we designed 3 modules to measure smoke, light and temperature from corresponding sensors. In the data reception stage, the received data are processed, the ADC is converted to probability values, combinational rules are performed twice, the related data are written into a TXT file, and the data are stored in the database. The processing steps are illustrated in Fig. 2. Finally, the final action taken is to judge whether a fire event is occurring. If the fire is real, the system enables a web page to display the data from the database, shows the tabular on the user's smartphone app, and sends a short message to notify the user.

The sampling rate of the sensor in this system is 1 unit

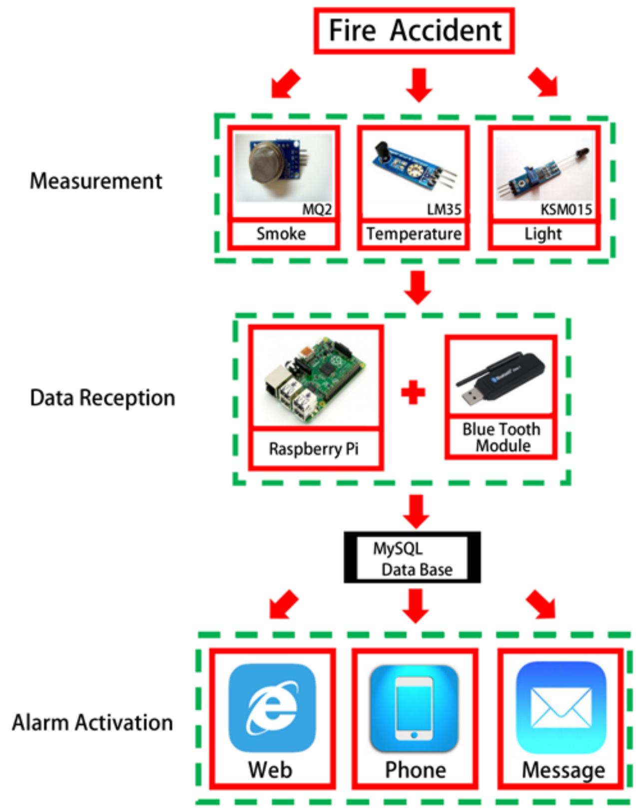

Fig. 1 System architecture

of data per second. In the detection module, we need to explain the procedure in more detail for ADC. For the temperature sensor, the range of measurement is between 0°C and 100°C. We set 70°C as the threshold value for a fire. Thus, the probability of the temperature is the measured value divided by 70. For the smoke sensor, the measured value for the range of the analog output is between 0 and 255. After validating the tests, the normal value of the No-fire phase shows approximately 100. Thus, the probability of the smoke sensor is the measured value multiplied by 0.00365. The range of the analog output is between 0 and 255 for the light sensor –the large value indicates the darkness. Thus, we need to modify the probability of the light sensor to be 1 − (the measured value divided by 255) = 1−(measured value *0.0039).

In the judging criteria for a fire, we set the continuous_times value to 5. While P(Fire) > 0.9 and K conflict < 0.8 hold, on the 6th, the system sets it as dangerous in the database.

3. Research Method

Multi-data fusion is often used to integrate the information from multi-sensors, and it has the merits of combining sensors together to improve the efficiency and accuracy of the system. Currently, there are many well-known data fusion algorithms such as the Dempster-estimation method, the Kalman filter and so forth. Among these options, the

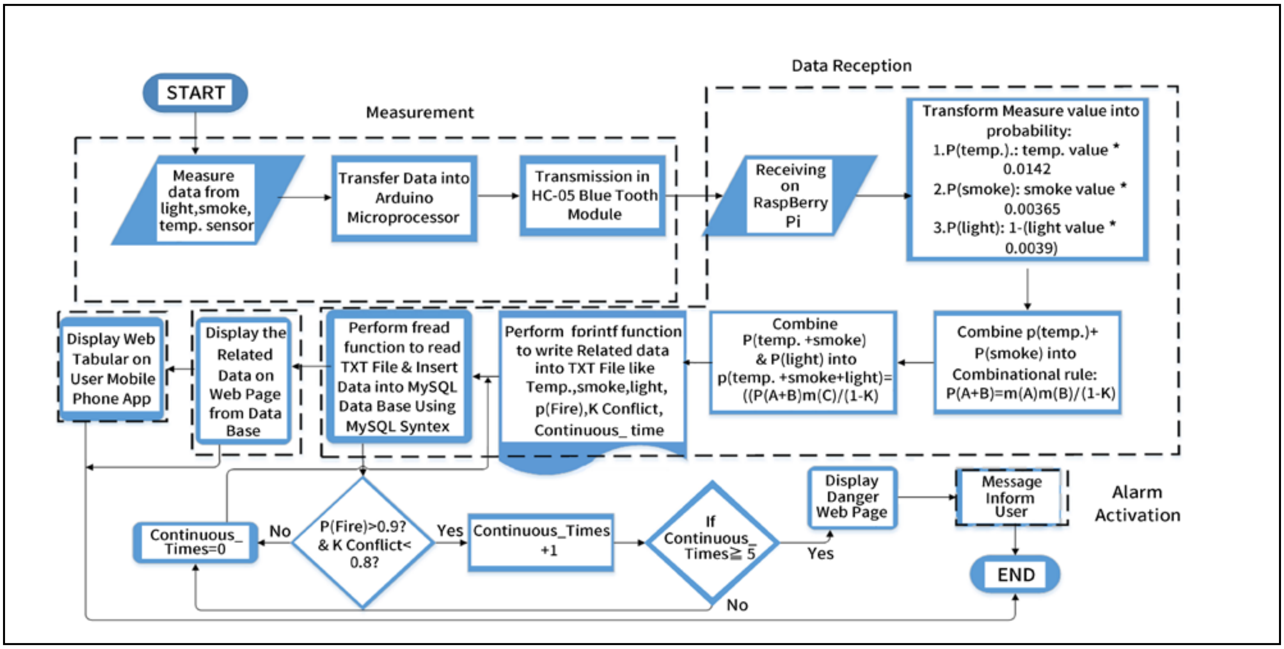

Fig. 2 System operating flow chart

Dempster-Shafer theory is well-known to solve the problem of uncertainty, match the behavior of people's thought, logic and decision making of inference. Furthermore, it is easy to calculate and easy to implement in programming.

In this article, we use the data fusion algorithm known as the Dempster-Shafer evidence theory, to analyze the measured data from the multi-sensor array and the combinational rule of conflict coefficient to minimize the uncertainty interval gradually. The Dempster-Shafer evidence theory was proposed by Arthur P. Dempster in 1967. Afterwards, Glenn Shafer finished the supplement to the theory. The Dempster-Shafer theory is an extension to the Bayesian theory and is efficient in solving the uncertainty problem. The fundamental knowledge and functions explanation is as followings:

3.1 Frame of Discernment (Θ)

The Frame of discernment presents all the elements of the event. All the elements should be completely mutually exclusive to each other. Being mutually exclusive to all elements means the elements cannot happen at the same time, i.e. the element within the flame cannot be duplicated. When the amount of frame elements is n, the frame size is $2^n - 1$. We set A as the element of the frame, then: $A \subseteq \Theta$ and $A \neq \emptyset$, and m (A) > 0 where A is an event or a piece of evidence.

3.2 Basic Probability Assignment Function (BPAF)

The BPAF value exists in the interval [0, 1], which represents the believability level of the event. This means the probability value of the event is termed as m(A). BPAF is different from traditional probability. Taking the frame Θ: {A,B,C} for example, in traditional probability, P(A) + P(B) + P(C) = 1 holds; it is the value of probability traditionally. However, for BPAF, when $m(A) + m(B) + m(C) \leq 1$ it still holds. The event is still within the interval to represent. BPAF satisfies the following criteria:

$$m : 2^{\theta} \rightarrow [0, 1]$$

$$m(\emptyset) = 0 \tag{1}$$

$$m(A) \geq 0, \forall A \in 2^{\theta} \tag{2}$$

$$\sum \left\{ m(A) \,\middle|\, A \in 2^{\theta} \right\} = 1 \tag{3}$$

3.3 Believability Function (Bel)

The believability function describes how much evidence supports this event or the belief that this event exists or is correct. A BPAF value of Sect. 3.2 is local belief, but this bel is more of a global belief which means the summation of the degree of believability from all evidence of this event, in other words, it stands for the summation of all BPAF's in the event. The formula is defined below:

$$Bel : 2^{\theta} \rightarrow [0, 1] \tag{4}$$

$$Bel(A) = \sum_{B \subseteq A} m_x(B) \tag{5}$$

3.4 Plausibility Function (Pl)

The plausibility function describes how many pieces of evidence can prove the level of believability of the event. Meanwhile, it includes uncertainty, double, contradiction and conflict. It represents the total believability level of the event which is not false. The function is defined below:

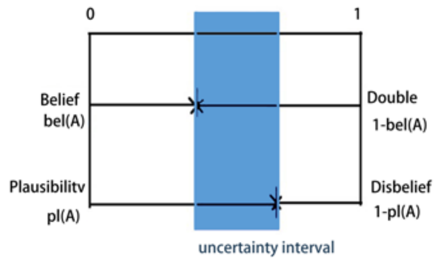

Fig. 3 Diagram of uncertainty interval

$$Pl : 2^{\theta} \rightarrow [0, 1] \tag{6}$$

$$Pl(A) = \sum_{B \cap A = \varphi} m_x(B) = 1 - Bel(\overline{A}) \tag{7}$$

3.5 Belief Interval

The belief interval can clearly represent the interval between not fully believing and not fully denying the evidence, [Bel (A), Pl (A)]. Pl (A) is the upper boundary and Bel (A) is the lower boundary of the uncertainty interval [11].

3.6 Combinational Rule

The Dempster-Shafer is proposed as an orthogonal rule of sum to compose the BPAF from different sources. The main aim is to reduce the uncertainty interval gradually and solve the contradictions and conflicts among the pieces of evidence. Finally, it synthesizes the information of several pieces of evidence into a single result. The following is the formula of the combinational rule:

$$m_x \bullet m_y(S) = \frac{\sum_{A \cap B = S} m_x(A) m_y(B)}{1 - \sum_{A \cap B = \varphi} m_x(A) m_y(B)} = \frac{\sum_{A \cap B = S} m_x(A) m_y(B)}{1 - K_{Conflict}} \tag{8}$$

where $M_x \cdot M_y$ is the probability of the same opinion to divide (1- the probability of different opinion).

$$K_{Conflict} = \sum_{A \cap B = \varphi} m_x(A) m_y(B) \tag{9}$$

where S means the same opinion for the event and $K_{Conflict}$ stands for the unreasonable or abnormal levels among the pieces of evidence, and its value exists in the range of [0, 1]. If the conflict coefficient K equals 1, it means there are pieces of evidence with serious contradictions and conflicts violating the real status. The lower $K_{conflict}$ is the most consistent of all the pieces of evidence. The result reflects the real status.

4. Results and Analysis

In the validation phase, we proceed to the field to collect realistic statistics in the daytime and nighttime. Experiments were performed under a controlled, safe, indoor environment by emulation of a fire event. From experimental results, two items arose to be discussed: the probability of a fire happening and the conflict coefficient $K_{conflict}$. Each experiment goes through the 3 phases: No-fire, On-fire and Post-fire. The experiment flow chart is illustrated in Fig. 4.

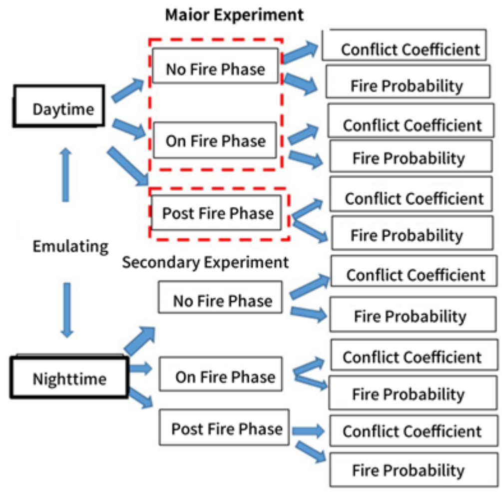

Fig. 4 Chart of emulating experiment phases

Table 1 Accuracy rate for daytime and nighttime with K=0.7

Daytime	Accuracy Rate
No-fire + On-fire Phase	97%
No-fire+ On-fire+ Post-fire Phase	93%
Nighttime	**Accuracy Rate**
No-fire +On-fire Phase	95%
No-fire+ On-fire+ Post-fire Phase	85%

Table 2 Accuracy rate for daytime and nighttime with K=0.75

Daytime	Accuracy Rate
No-fire + On-fire Phase	97%
No-fire+ On-fire+ Post-fire Phase	95%
Nighttime	**Accuracy Rate**
No-fire+ On-fire Phase	96%
No-fire+ On-fire+ Post-fire Phase	86%

4.1 Discussion of the Value of $K_{conflict}$

We stress that the conflict coefficient of the Dempster-Shafer theory will slightly affect the final result of the experiment and its accuracy. Accordingly, field test is a reliable way to set conflict coefficient and so as to improve the system accuracy rate. Setting the value raises the judgement criteria by decreasing the value of the conflict coefficient. The following is to check on the system accuracy rate by modifying the conflict coefficient:

- Modify the conflict coefficient to be 0.7
- Modify the conflict coefficient to be 0.75

Adjusting the conflict coefficient to a lower value of 0.7 means raising the criteria of judgement. Our detection system still keeps an accuracy in the range of 80% to 90%. The same results show up after adjusting K conflict to be

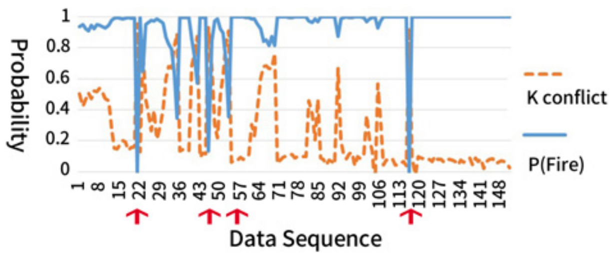

Fig. 5 Daytime on fire phase: P(Fire) vs. $K_{conflict}$

0.75 without obvious.

After real testing, we set the $K_{conflict}$ to 0.8 as the pivot point which shows the higher accuracy of our implement in major experiments during daytime amounts 98% and the accuracy during nighttime reaches to 97%. While $K_{Conflict} > 0.8$, the result shows it does not seem to be reasonable. Therefore, we select the $K_{conflict}$ to be 0.8 as the better choice after experimental statistics.

4.2 Daytime Experiment

The experiments are undergone in two groups to process: one is the major group and the other is the secondary test. In the daytime part, the major experiment contains the No-fire phase and the On-fire phase. The secondary experiment in the daytime part contains only the post fire phase. For both the major and secondary part within the simulation, the following step is to calculate the conflict coefficient and fire probability.

4.2.1 Major Tests

1. Daytime No-fire:
   The probability of a fire happening is rather high, but the K conflict remains at 0.6 during the daytime under the No-fire phase. Therefore, it surely reflects the real status. During the daytime, it is under bright environment and the values of P(Fire) remain in the higher range between 0.8 and 0.9, but the $K_{conflict}$ is approximately 0.6. So, it is surely near the real status.
   Shortening the interval of the x-axis into [0.75, 1], we proceed to the observation step. Although P(Fire) is higher, we find P(Fire) still below 0.9 in general. It could not interfere with the detection that has set the base value of a fire as 0.9.
   In Fig. 5, it demonstrates P(Fire) vs. $K_{conflict}$ during the daytime On-fire phase. There are four cases of P(Fire) dropping, marked by a dark arrow, and the $K_{conflict}$ rising suddenly, which are both abnormal cases apparently. We find the values variate violently in the On-fire phase but the value is stable in the No-fire phase. During the daytime, P(Fire) exists within the interval of [0.9, 1]. The variant range of $K_{conflict}$ during the daytime during the On-fire phase is larger than that of the No-fire phase.
2. Nighttime On-fire Phase Experiment:

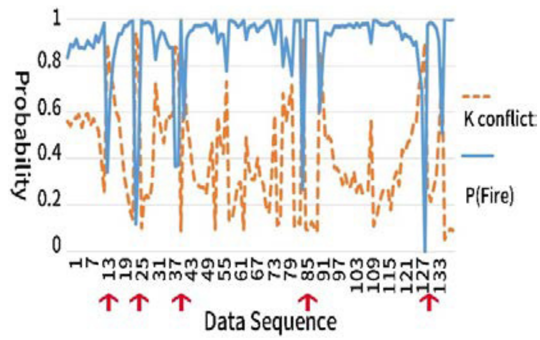

Fig. 6 Nighttime phase on-fire phase: $K_{conflict}$ vs. P(Fire)

   During the nighttime Post-fire phase, both P(Fire) and $K_{conflict}$ are found in the extreme low bank, lower even than 0.1. During the nighttime, $K_{conflict}$ is found in the range of 0.4 and 0.5 which is within the normal status as long as the $K_{conflict}$ stays below 0.8.

4.3 Daytime vs. Nighttime

4.3.1 Daytime

According to the plan of the field tests, we proceed the detailed discussion in three phases as following:

a. No-fire phase:
   During the daytime under brighter environment, P(Fire) is higher than the probability of fire during the nighttime. Our statistics show only two records that were higher than the base probability value 0.9. Furthermore, these two cases did not happened in adjacent sequence, which does not meet the criteria of the continuous_times which is required at 5 times with P(Fire) larger than 0.9. As for the K conflict, there is no case higher than 0.8, although it is higher during the daytime than the nighttime. Thus, we conclude it is of normal detection in the no-fire phase whether during the daytime or the nighttime.
b. On-fire phase:
   Whether in the No-fire or On-fire phase, P(Fire) during the daytime has a higher probability of remaining at P(Fire)=1. While P(Fire) is higher during the daytime than the nighttime, whether in the No-fire or On-fire phase the detection still proceeded well.
   During the On-fire phase, there were only eight records of the $K_{conflict}$ exceeding 0.8 during the daytime and nine records during the nighttime. Thus, this impact is beyond the significant.
c. Post-fire phase:
   The blue line represents the P(Fire) as shown in Fig. 7 during the post-fire phase in the daytime. Most of the values are above 0.9 because it has a high measured value detected by the light sensor and the heat was not abating. These reasons resulted in the P (Fire) remaining above 0.9. The red dashed line stands for the

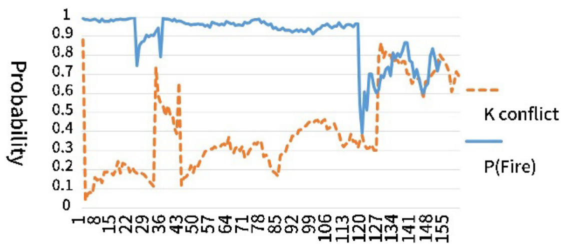

Fig. 7 Daytime post-fire $K_{conflict}$ vs. P(Fire)

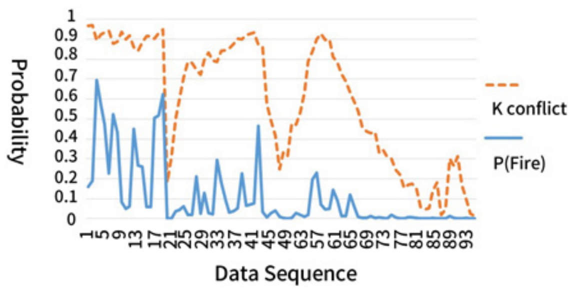

Fig. 8 Night time & post-fire: $K_{conflict}$ vs. P(Fire)

$K_{conflict}$ values in the post-fire phase during the daytime.

4.3.2 Nighttime

Based on the time codes, we can see P(Fire) approaching zero in Fig. 8. The red dashed line stands for the $K_{conflict}$ in the Post-fire phase during the nighttime.

It shows most of the $K_{conflict}$ values distributed above 0.8. After observation, fire is extinct while the flame becomes dimmer and dimmer. During this period, the flame sensor reports a higher value indicative of growing darkness in the environment, meaning less likelihood of fire. In the meanwhile, high temperature lasts and smoke remains thick. It results in the contradiction between the pieces of evidence.

From the observed data, it shows that the $K_{conflict}$ during the daytime is lower than in the nighttime. From the factors of bright light and temperature not abating, the P(Fire) remains at a high probability value. Conversely, the probability of a fire is quickly approaching zero.

4.4 Results

- Daytime Results in Tabular:
- Nighttime Results in Tabular:
- Accuracy Rate in Daytime:
- Accuracy Rate in Nighttime:

The observe time intervals are shown in Table 3 and Table 4 within 2 to 4 minutes. Meanwhile, from the statistics of Table 5 and Table 6, the accuracy rate for daytime and nighttime are 97% and 89%, respectively. Thus, for the whole system, the total accuracy rate is near 90%.

Table 3 Daytime results

	No-fire Phase	On-fire Phase	Post-fire Phase
Record Number	223	151	161
Observe Time Interval	4 Min.	3 Min.	4 Min.
Record No. for K conflict>0.8	0	8	6

Table 4 Nighttime results

	No-fire Phase	On-fire Phase	Post-fire Phase
Record Number	181	137	94
Observe Time Interval	4 Min.	3 Min.	2 Min.
Record No. for K conflict>0.8	0	9	37

Table 5 Accuracy rate in daytime

Experiment Phase	Accuracy rate
On-fire	94%
No-fire+ On-fire	98%
Post-fire	96%
No-fire+ On-fire+ Post-fire	97%

Table 6 Accuracy rate in nighttime

Experiment Phase	Accuracy rate
On-fire	93%
No-fire+ On-fire	**97%**
Post-fire	61%
No-fire+ On-fire+ Post-fire	89%

5. Conclusion

In order to better expose the novelty of this research, we highlight the following aspects in which this study distinguishes itself from most literature.

- A fewer number of essential determinants have been identified for efficient fusion and for accurate deductions. Our design and implementation enable the deduction process to react reliably yet correctly to emergency events in real-time.
- As far as data fusion in our architecture is concerned, determinants result from moderate interpretations of three sensors' readings. Three determinants are then quantified as different degrees of belief regarding fire that serve the purpose of inputs to Dempster-Shafer theory.
- We leverage the use of Dempster-Shafer theory but keep operations neat wherever possible. Under our consideration are two orthogonal hypotheses: fire and non-fire incidents. The plausibility of a hypothesis can be assessed directly by 1 minus the mass of a given proposition. The mass associated with either hypothesis can be simplified as well. While combining beliefs, the joint mass can be obtained through simple table look-up without involved computations.
- Our design has been implemented over the platform of Raspberry Pi, Arduino, WiFi, Bluetooth modules, and sensor units with necessary circuits. We have also set up a web server plus a MySQL database co-located at

the Raspberry Pi that keeps all the reported data from sensors and our deduction results in storage. An Android APP has been developed to connect over the Internet to the web server for remote access and for text message (SMS) notification in the event of fire.
- Our implementation has been put into practical use for fields tests to collect experimental results. Experiments were conducted to mimic real-life situations by setting up fire in a safe controllable environment. We observe how our implementation reacted in different periods of no-fire, on-fire and post-fire during day-time and night-time, respectively. We believe that our experimental results are convincible enough to validate our development.

To a great extent, our design and implementation corroborate the usefulness of applying D-S theory to multi-sensory fusion in pragmatic situations.

Although P(Fire) is higher for the bright light in the daytime, we could not judge the fire's occurrence only by the light without all the other criteria. It is not by the light sensor only that we judge the fire's occurrence. The proposed system does not have false judgement resulting in a false warning, which means that the system's accuracy is not affected. In the daytime and nighttime, the accuracy rates of the No-fire and On-fire phases are almost the same. However, the accuracy rate during the daytime is higher than in the nighttime during the Post-fire phase. For all phases, the accuracy of the system reaches 90%. Furthermore, the proposed system provides real time short message services. The entire system is built on reliability and efficiency.

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