Asian Journal of Science, Engineering and Technology (AJSET)
eISSN: 3006-6980 (online)
https://www.ideapublishers.org/index.php/ajset
Vol. 3, No. 1 (January-December), 2024, pp. 135-150
https://doi.org/10.47264/idea.ajset/3.1.9
Original Research Article

Assessing the fidelity of ultrasonic distance sensors in fire-and-smoke environment

Shaheer Muhammad[1] | Hannan Adeel[1] | Tahir Saleem Khattak*[1] | Inamur Rehman Rao[2] | Shamaila Hayat[3]

1. Department of Computing, Hamdard University, Islamabad Campus, Islamabad, Pakistan.
2. Department of Information Technology, Hamdard University, Islamabad Campus, Pakistan.
3. Department of Computer Science, University of Poonch, Rawlakot, Azad Jammu & Kashmir, Pakistan.

*Corresponding Author Email: tahir.saleem@hamdard.edu.pk

Article History

Received:
10-Oct-2024

Revised:
13-Nov-2024

Re-revised:
14-Dec-2024

Accepted:
15-Dec-2024

Published:
31-Dec-2024

Abstract:
Lack of visibility in fire-and-smoke environments is a major factor that causes operational difficulties, injuries, and loss of life in firefighting. To counter this problem, distance or range-finding sensors are used to detect obstacles or map out the area in fire and smoke environment. These sensors can be mounted on robots assisting firefighting or even firefighters themselves. This paper aims to assess the operational capability of ultrasonic distance sensors in fire-and-smoke environments. Moreover, we investigate how to extract useful information in limiting conditions. Specifically, we design experiments to test Sonar's range-finding abilities, which are interfered with by burning different types of fuels. The experiments are performed for smoke without flame (smoke pallets), flame without smoke (propanol), and flame with smoke (kerosene) at different distances from Sonar. The results show that Sonar is very effective in smoke because smoke without flame does not increase the air temperature significantly. However, if interference consists of flame, air temperature increases; thus, Sonar outputs erratic data. This study analysed this erratic output of Sonar and provided a filtering algorithm that can eliminate the erratic and stray values from Sonar output and provide valuable information that is helpful in navigation, mapping, or obstacle detection.

Keywords: Sonar detection, Sensor, Obstacle, Firefighters, Filter, Robot, Structural fire, Propanol, Kerosene, Range finding sensors, Distance sensors, Firefighting.

How to Cite: Muhammad, S., Adeel, H., Khattak, T. S., Rao, I. R., & Hayat, S. (2024). Assessing the fidelity of ultrasonic distance sensors in fire-and-smoke environment. *Asian Journal of Science, Engineering and Technology (AJSET), 3*(1), 135-150. https://doi.org/10.47264/idea.ajset/3.1.9

1. Introduction

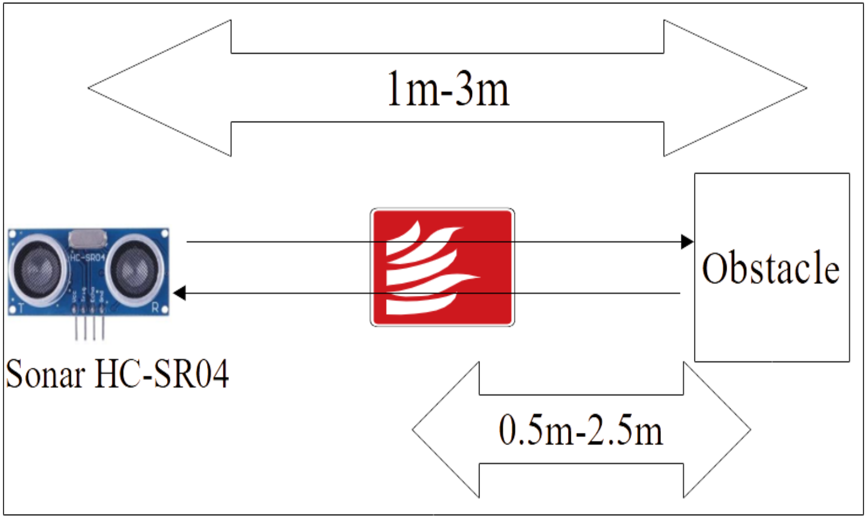
Structural firefighting is one of the dangerous tasks which cost many lives of firefighters each year. Around 100,000 structural fires cost 1.8 firefighter lives in the year 1977, and this number increased to 3 in 2000 (Carr-Pries *et al.*, 2022). Approximately 33% of all fires are structural fires (Karter, 2013), and most dangerous structural fires occur in large structures like industrial plants, warehouses, or high-rise buildings (Fahy *et al.*, 2017; Haynes, 2017). Burns, inhaling smoke, getting trapped, or overexerting are common conditions encountered in 'fire and smoke environments' resulting from structural fire (Karter, 2009; Campbell, 2018). Two phenomena are common in structural fires. The first is the flashover point, known as a stage during a fire when all the combustible surface in a room burst into flames, and the second is backdraft, known as a smoke explosion, that is caused by a sudden influx of air in a room where combustion has been occurring in a shortage of air. Both these phenomena are dangerous events and depend on the ventilation of a room or a building. Therefore, knowing the location and orientation of doors and windows can help firefighters avoid injury (Gorbett *et al.*, 2007; Zhang *et al.*, 2014). Many studies focused on limiting firefighters' exposure to dangerous and severe conditions encountered in fire and smoke environments caused by structural fires (Pawer *et al.*, 2022). Firefighting mobile robots and Unmanned Aerial Vehicles (UAVs) have been used to assist firefighters (Wang *et al.,* 2017; Imdoukh *et al.*, 2017). Most firefighting assistant robots or UAVs (Wang *et al.*, 2024) are not designed for indoor or structural firefighting because most rangefinder technologies that these robots rely on for navigation are heavily affected by the environment conditions in the fire and smoke environment.

There has been progress in understanding the challenges of designing fire safety, particularly in terms of effectiveness and formulations of fire detection and safety in certain applications, a considerable focus remains on the well-being of building occupants (Meacham, 2022). The current fire protection systems primarily employ detectors for smoke, temperature, gas, flame radiation, and air pressure. However, the sensitivity and automation of these detectors in the existing system do not fully meet the requirements for the information age (Song *et al.*, 2022). State-of-the-art fire prevention and detection systems utilise technologies based on SLAM, LiDAR, depth cameras (Balen *et al.*, 2023), acoustic detection (Wang *et al.*, 2023), and deep learning techniques (Abdusalomov *et al.*, 2023). While during firefighting, rangefinder technologies like Sonar, LiDAR, thermal camera or 3D camera can be used by assistant robots to detect, range and avoid obstacles, localise landmarks, find free space to navigate, and for object recognition depending on the device. Algorithms tailored for firefighting can be used in conjunction with these rangefinder devices to map the area and provide invaluable information about the environment, for example, whether doors and windows are open or shut.

Evaluating the effectiveness of these rangefinder technologies in fire and smoke environments brings us one step closer to better firefighters' safety. Numerous innovative fire detection systems have been developed to increase sensing systems' detection capabilities and reduce false alarms. For buildings, actuator-based fire detection systems were designed to indicate the necessary modifications for fire safety. Heat sensing systems are more dependable and produce fewer false alarms but react slowly. In most of the literature, optical heat sensors are utilised extensively in tunnels and mines. Nonetheless, they work best in settings with galleries, large rooms, and intricate areas. It can lower the cost and replace the need for several-point heat sensors throughout a structure. Vision-based fire, flame, and smoke sensors are used in addition to non-visual fire sensing techniques. Wireless Sensor Network (WSN) based fire detection systems install detectors as detector nodes with integrated communication hardware. The main challenge is making them stable, error-tolerant, and low-power. Comparing deep learning to conventional computer vision techniques, greater accuracy can be achieved in fire detection, which includes picture classification, semantic segmentation, object identification, and simultaneous positioning.

A new area of study has emerged because of using robots in fire detection. While they can't replace human firefighters because human intelligence is greater than that of robots, firefighting robots will support human firefighters in their duties (Khan *et al.*, 2023). Few studies have evaluated these rangefinders or distance sensors. One study evaluated the most used sensors, such as IR cameras, Sonar systems, LiDARs, depth cameras and night vision camera in fire smoke environment. Experiments were performed to show the performance and failure points of each sensor. The results show that depth camera and night vision cannot perform adequately in fire and smoke environments. LiDAR cannot work in dense smoke and is not affected by the temperature. Sonar is heavily affected by temperature but is unaffected by smoke (Peterson *et al.*, 2020). Sonar is a time-of-flight sensor that sends a sound wave of a particular frequency toward an obstacle and times how long it takes to return. Flight time of sound wave can be used to find the distance from the obstacle. It is cheap, lightweight and a commonly used sensor in many range-finding and navigation applications (Najm *et al.*, 2024) (e.g. UAVs and mobile robots).

Figure 1: An illustration of experimental setup



Few other studies have also evaluated Sonar in the smoke environment. Sonar system was used to detect and follow a person in a smoke environment (Jones *et al.*, 2019). The smoke was artificially created by using glycol-based fog. The density of smoke was measured using a visual smoke detection system. As glycol-based liquid droplet fog smoke is generally at room temperature and is in the form of small droplets, it has very different properties from smoke from fire, which has higher temperatures and different particulates. As Sonar uses sound waves for detection, the temperature of the medium becomes an important factor of evaluation (Thompson & Daniels, 2018). To evaluate Sonar, Peterson *et al.* (2020) used only two types of interference which are low-temperature dense smoke and high-temperature with low density smoke. This study aims to build upon work presented by Peterson *et al.* (2020) on Sonar and look at the performance of Sonar in fire and smoke environments in more detail. Specifically, we evaluate sensors with smokeless flame, flameless smoke with three densities (low, medium and high), and flame with smoke with three densities.

Firstly, the experimental setup is designed to evaluate Sonar in various scenarios. Then, for each scenario, fire and smoke interference is moved near or far from the Sonar to observe the change in measurement caused by interference. Performance and failure points are shown through experimental results. Empirical data is analysed, and the advantages and disadvantages of Sonar as a potential range finder technology in a fire and smoke environment are discussed. Moreover, a simple filtering algorithm is proposed, which improves Sonar output in the presence of interference and makes it usable.

2. Proposed experimental setup

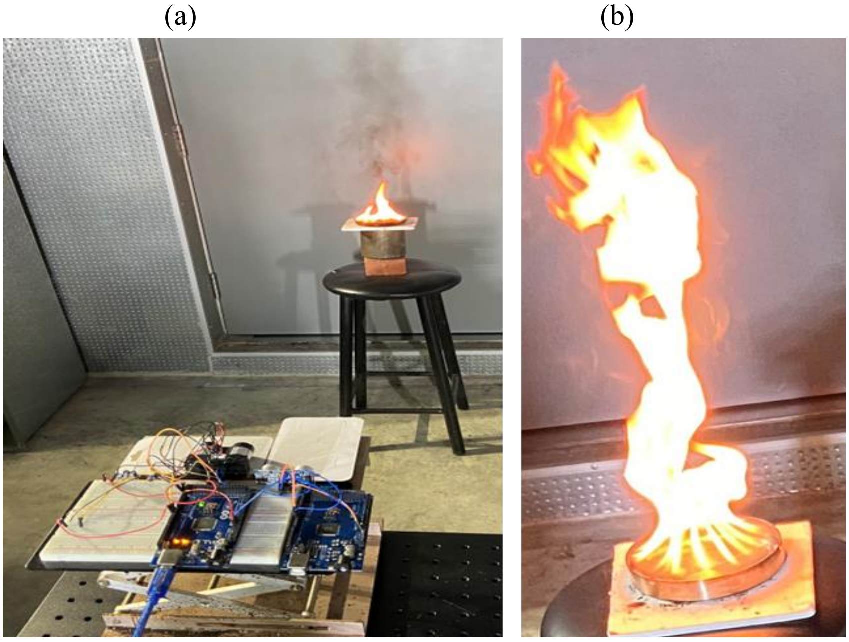
2.1. Overview

The proposed experimental setup consists of three parts.

- Sonar: it is a sensor being evaluated.
- Interference: Interference is the disturbance that simulates conditions of structural fire. Three types of interference are used in this setup: smokeless flame, flameless smoke, and fire with smoke.
- Obstacle: It is an immovable structure placed in the line of sight of the Sonar. Sonar can easily detect obstacles under normal conditions.

Initially, the Sonar is placed at 1m from the obstacle without any interference. The distance value is measured and called the nominal value. Next, three types of interference are placed at 0.5 m from the obstacle, and the value is recorded. Sonar is then moved to 1.5 m from the obstacle, and the nominal value is recorded. Now, interference is placed at 0.5 m from the obstacle and after recording the value, it is moved away from the obstacle towards Sonar to 0.5 m and new Sonar value is recorded. In every round of the experiment, the Sonar is moved away from the obstacle 0.5 m and interference is placed between obstacle and Sonar at every 0.5 m interval one by one. This process is repeated until Sonar reaches 3 m from the obstacle and at every step nominal and affected values are recorded. Figure 2 shows the illustration of the experimental setup.

Figure 2: (a) Experimental setup hardware, and (b) 2-Propanol smokeless flame



2.2. Hardware

Sonar HC-SR04 ultrasonic range finder is used as sensor for evaluation. This Sonar operates on 5V DC and has a working current of 15 mA. It can provide distances between 2 cm to 3 m. The soundwave frequency is 40 kHz and has a measuring angle of approximately 15°. Sonar is connected to Arduino Mega 2560 which records the data. The hardware setup for experiments are shown in Figure 2a.

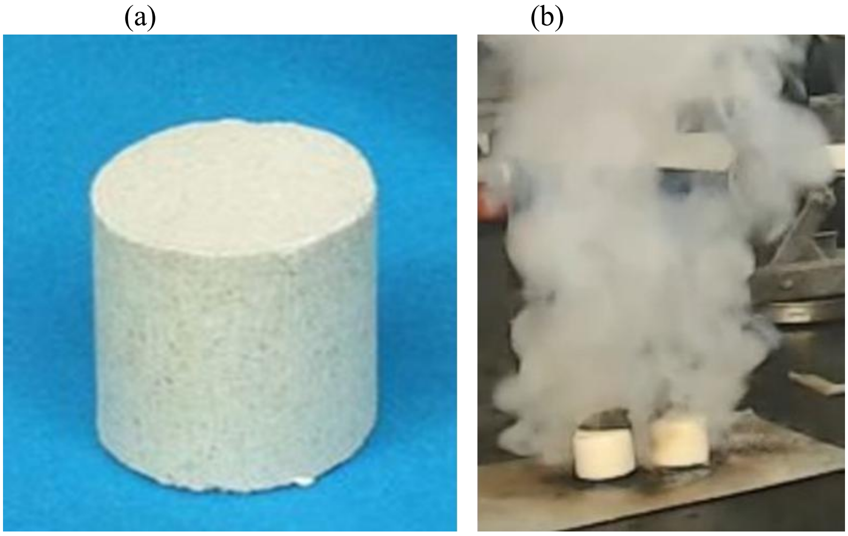
2.3. Interference

Three types of interference are used in the experiment. Each type is discussed below.

2.3.1. Smokeless flame: 2-Propanol

Propanol is a fuel that burns with minimal, almost invisible smoke as shown in Figure 2b. The typical flame temperature of 2-Propanol smokeless flame at the detection level is around 800 °C. This flame spikes the temperature of the surrounding air significantly. As in this case, Sonar uses air as a medium to send sound waves to detect obstacles, so air temperature becomes an important factor in determining Sonar's performance. This interference simulates high-temperature fires and the smoke environment in structural fires.

Figure 3: (a) Smoke pellet, and (b) Flameless smoke produced by burning smoke pellet



Structural fires typically consist of different types of fires. One example of smokeless flame is ethanol flame, commonly present in many structures.

2.3.2. Flameless smoke: smoke pellets

Smoke pellets, as shown in Figure 3a, can emit smoke without any flame. This interference simulates the scenarios of hallways in structural fires where smoke accumulates, and visibility decreases significantly. Smoke pellets are used to simulate this condition. The smoke pellet used in this experiment emits approximately $7m^3$ in 30 seconds. One smoke plume has an average diameter of 10 cm, as shown in Figure 3b. Three densities (low, medium, and high) of smoke are used as interference. At the detection level, the temperature of the smoke is approximately 40 °C.

2.3.3. Flame with smoke

In this experiment, we use two types of flame with smoke interference: (1) We use kerosene as fuel for high-temperature flames and black smoke, as shown in Figure 4a. Kerosene burns with a high temperature of about 700 °C, at a detection level with black smoke, and (2) For flame with white smoke, we burn smoked pellets with 2-Propanol, as shown in Figure 4b.

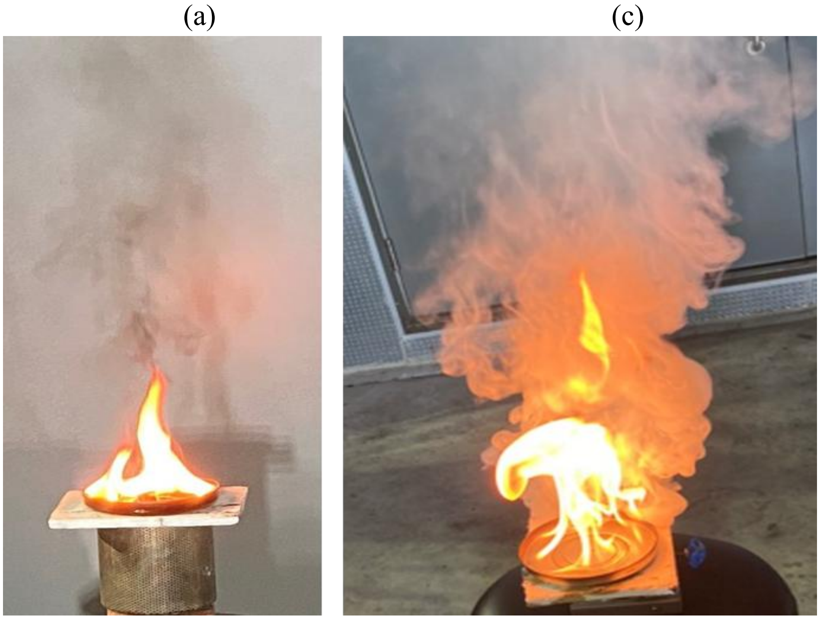
2.4. Smoke density measurement setup

Smoke can be quantified by measuring its transmittance (Green *et al.*, 2017). Transmittance of smoke τ is defined as the ratio of light intensity measured through the smoke I, to the light intensity measured without smoke I_0. Transmittance depends on three factors: mass density of smoke d_m, length of optical path l, and specific light extinction coefficient, σ_s. Equation (1) shows this relationship described by Bougher-Lambert-Beer law.

$$\tau = \frac{I}{I_o} = e^{-\sigma_s d_m l} \tag{1}$$

For this experiment, we designed a smoke measurement setup that consists of 850 nm wavelength, 3.5 mW laser, and photodiode, as illustrated in Figure 5. The operation of this smoke measurement setup is simple; the value of the photodiode is measured without any smoke obstruction, I, and then with smoke obstruction, I_0. The ratio of these two values gives the transmittance of the smoke plume. The measured transmittance of low, medium, and high-intensity smoke is 0, meaning that smoke plumes of even low density are thick enough that visibility through the plume is zero.

Figure 4: (a) Burning kerosene showing black smoke, and (b) Burning 2-Propanol and smoke



3. Results and discussion

In this section, we present experimental results. Sonar is inherently a noisy sensor. Even in near-ideal conditions, Sonar will produce some outliers due to noise or stray reflections. This phenomenon can be countered with simple filtering methods. First, we present the results without filtering to show the actual performance of Sonar, and then the same results are presented using the proposed filtering algorithm applied to Sonar readings. The operation of Sonar is based on the time of flight (ToF) of the sound wave that is emitted by the sensor at a particular frequency. The wave travels through a medium, which in this case is air, hits the obstacle and reflects back to the sensor. The ToF of the sound wave measures the distance from the obstacle.

3.1. Sonar in the presence of flameless smoke

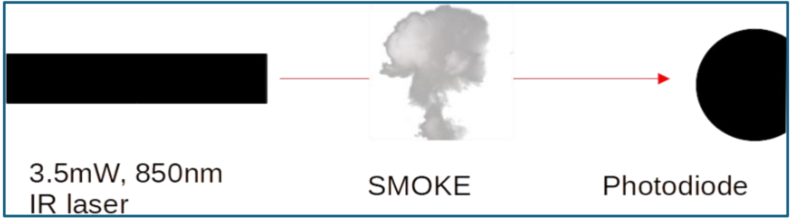
Flameless smoke is generated using a smoke pellet. This smoke does not increase the air temperature too much because there is no flame. The temperature of smoke at the line of sight (LoS) of Sonar is around 40 °C to 50 °C. Sonar values are measured through the smoke at a point where the thickness of the smoke plume is the highest. Results show that smoke without any flame does not affect the values of Sonar too much. Figure 6a shows how Sonar is affected when different densities of smoke are present. In this experiment, Sonar is placed at 1 m from the obstacle, smoke interference is placed between Sonar and obstacle at 0.5 m, and three sets of readings are obtained. In the first set of readings, interference is one smoke pellet (light smoke). Two smoke pellets (generating medium smoke) are used in the second set of readings. Similarly, three smoke pellets (generating heavy smoke) are used for the third set of readings. It can be seen in Figure 6a that there is little difference between the nominal value and values with interference near Sonar. It is hardly affected by the smoke.

Standard deviation can be calculated to see how much effect the increasing density of smoke has on Sonar. Table-1 (row 1) shows the standard deviations for different smoke densities. Even in heavy smoke there is little deviation in Sonar value. Standard deviation is calculated as using Equation (2).

$$\sigma = \sqrt{\frac{\sum x_i - \mu}{N}} \tag{2}$$

Where σ is the standard deviation, N is the number of readings, x_i is the i^{th} value of Sonar, and μ is the mean of all the values. It should be noted that this is the standard deviation of unfiltered values from Sonar. A slight increase in standard deviation observed as the smoke density is increased, as shown in row 1 of Table-1, may have been caused by factors such as slight air temperature increase caused by burning smoke pellet or change of medium from air to air plus soot. These factors must be explored in further studies. However, this slight increase in standard deviation is negligible and can be ignored because Sonar values are filtered and averaged in practice, which further decreases the standard deviation.

Figure 5: Smoke measurement setup



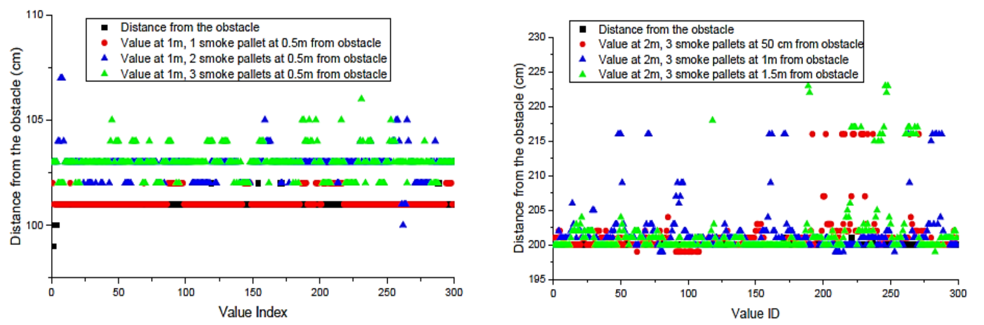
Sonar is commonly used on many mobility platforms such as UAVs, and to thoroughly evaluate its effectiveness in a smoke-filled environment, it is important to test how Sonar values change regarding the distance from smoke interference. To do this, Sonar is placed at 2 m from the obstacle, and high-density smoke is placed at 50 cm from the obstacle. Then, it is moved to 1m from the obstacle and finally to 1.5 m from the obstacle. This is done to determine how Sonar values will change if the obstacle, the target to be detected, is covered with smoke or UAV with Sonar flies in the smoke plume. The results of this experiment are shown in Figure 6b. Sonar has little difficulty detecting obstacles regardless of the placement of smoke interference. The number of outliers increases as smoke moves towards Sonar, but it stays functional. To visualise this phenomenon, the calculated standard deviations are listed in Table-1 (row 2) for different measures of interference distance. There is a slight increase in standard deviation as smoke interference moves towards Sonar. The same effect is seen if Sonar is placed at 3m from the obstacle and smoke interference is placed at 50 cm, 1.5 m, and 2.5 m from the obstacle, as shown in Figure 6c Standard deviations for Sonar values placed at 3 m show the same trend that Sonar values show slightly more deviation as the smoke interference moves towards Sonar.

In this section, the results discussed use raw Sonar values. This is done to show Sonar's actual performance without the use of any filter. In practice, however, Sonar values are filtered to remove any outliers, which can further improve Sonar's performance in a smoke-filled environment. Simple filtering techniques can improve the results further as discussed in 3.5. Improved results after filtering can be seen in Figure 8b. As shown in row 5 of Table-1, standard deviation after filtering is also enhanced.

3.2. Sonar in the presence of smokeless flame

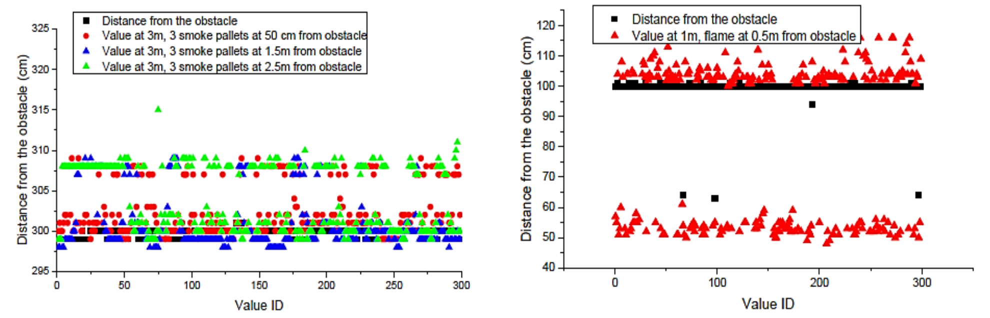
Sonar behaves quite differently in the presence of flame. This is because of increased air temperature, which hinders the nominal medium that Sonar is designed for. We performed a series of experiments to gauge Sonar's performance.

Figure 6: Sonar values concerning smoke densities and interference distance from the obstacle



(a) Sonar value at 1m, low, medium and high density smoke at 0.5m from obstacle.

(b) Sonar value at 2m, high density smoke at 0.5m, 1m and 1.5m from obstacle.



(c) Sonar value at 3m, high density smoke at 0.5m, 1m and 1.5m from obstacle.

(d) Sonar value at 1m, smokeless flame at 0.5m from obstacle.

The experimental setup is the same as that of Sonar in the flameless smoke investigation. In this series of experiments, smoke interference is replaced with flame interference, which uses 2-Propanol as fuel. It is smokeless, and its flame burns at around 2000 °C. Sonar is placed at 1m from the obstacle and flame interference is placed at 0.5 m from the obstacle. The result is shown in Figure 6d. Table-1 (row 4) shows the standard deviations for flame interference. At first glance, it seems that Sonar performed erratically with a deviation of approximately 25 points from base value. However, if the results are graphed as shown in Figure 6d, there is a clear pattern. In this case, Sonar returned two sets of values, one set of values provides the distance measurement of the obstacle, the target to be detected, while the other set of values shows the distance from the flame. One set of values is the distance from the flame because the flame distorts the medium with increased air temperature, so sound waves scatter, and instead of detecting the obstacle, the flame container reflects these sound waves.

This phenomenon of obtaining two distinct sets of values in the presence of flame is advantageous because it can be exploited. It is possible to filter the set of values based on the magnitude of values. For example, in Figure 6d, we can set a threshold of 10 cm and divide the values into two distinct sets and then choose the set with values with higher magnitude. It should also be noted that standard deviation analysis done on raw values will not yield any useful result. The next step is to see how Sonar behaves when flame interference is displaced between the obstacle and Sonar. This is done to see how Sonar will behave when it operates on mobility platforms such as UAVs. In this session, the Sonar is placed at 2 m and flame interference is placed at 0.5 m from the obstacle and then moved towards Sonar at 0.5 m increments. The results are shown in Figure 7a. Sonar returns two sets of values wherever the flame interference is placed. The same phenomenon is observed when Sonar is placed at 3 m from the obstacle as shown in Figure 7b. As the flame interference moves towards the Sonar with increments of 0.5 m, Sonar registers some unwanted values at every displacement.

Table-1: Standard deviations with respect to number of smoke pallets and distance of flame interference from the obstacle

Smoke densities measured at 1m	Nominal	1SP	2SP	3SP
	0.20849	0.38492	0.68224	0.75144
Interference distance from obstacle with 3SP at 2m	Nominal	50 cm	1 m	1.5 m
	0.11489	3.30235	3.87813	4.98717
Interference distance from obstacle with 3SP at 3m	Nominal	50 cm	1 m	1.5 m
	0.44651	3.16319	3.44529	4.00320
Flame interference	Nominal (unfiltered)	0.5 m (unfiltered)	Nominal (filtered)	0.5 m (filtered)
	0.22023	2.07009	3.98478	26.73900
Interference distance from obstacle with smoke (filtered)	Nominal	50 cm	1 m	1.5 m
	0.44651	3.16319	3.44529	3.93256

In the presence of flame, Sonar loses its effectiveness significantly due to high air temperature. However, useful information can still be extracted. It can be observed from the experiments that position of interference is not a big factor in Sonar performance. Flame, by raising the air temperature around it, affects Sonar's readings, and we get a mix of accurate and false values. In the case of smokeless flame, however, it is easy to differentiate between false and accurate values. Desired results can be obtained using simple filtering as discussed in section 3.5.

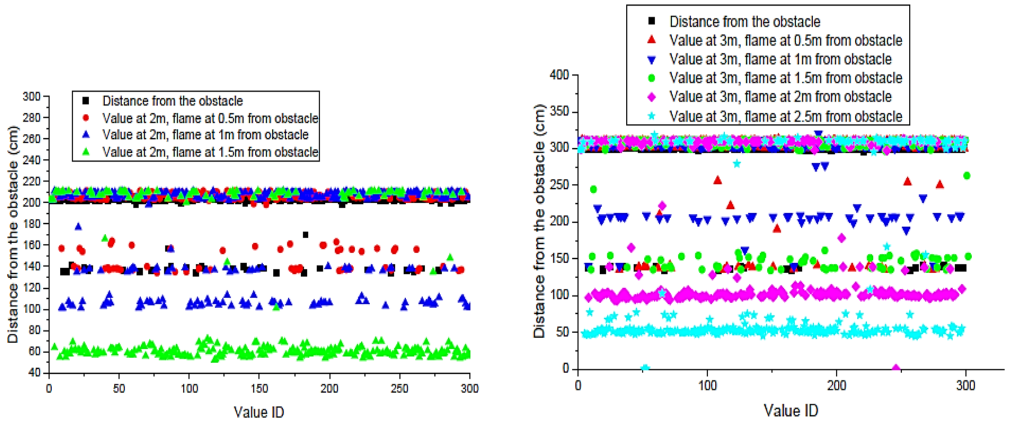
3.3. Sonar in the presence of fuel with smoke and fire

Structural fires can have different types of fires because of different materials that are present in structures. To simulate this, we used two types of interference: (1) Kerosene is used because it burns quite hot at 2000 °C and produces black smoke as shown in Figure 4a, and (2) 2-Propanol with smoke pellets is used to simulate fire heavy smoke as shown in Figure 4b. As expected, kerosene and 2-Propanol with smoke have the same effect on Sonar as smokeless flame as shown in Figure 7d and Figure 7c respectively. That is because, as discussed earlier, smoke does not render Sonar ineffective and due to higher air temperature, smoke produced by both fuels is dispersed quickly so there is negligible effect of smoke on Sonar in this case. However, the flame part of these fuels has the same effect as smokeless flame.

3.4. Speed of sound under different interference

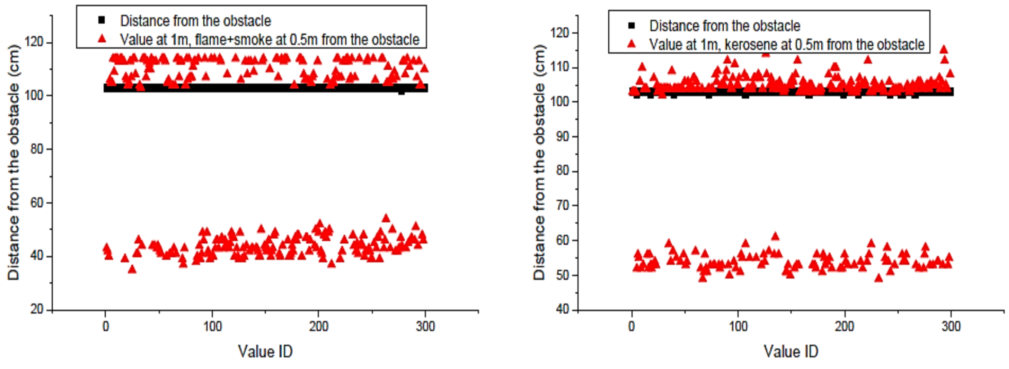
As mentioned earlier, the temperature of smoke without a flame is about 40 °C or 313 K, the temperature of the 2-proponal flame is about 800 °C or 1073 K, and the kerosene flame has a temperature of about 973 K.

Figure 7: Sonar values with respect to smoke densities and interference distance from obstacle



(a) Sonar value at 2m, smokeless flame at 0.5m, 1m and 1.5m from obstacle.

(b) Sonar value at 3m, smokeless flame at 0.5m, 1m, 1.5, 2 and 2.5m from obstacle.



(c) Sonar value at 1m, flame with smoke at 0.5m from the obstacle.

(d) Sonar value at 1m, kerosene at 0.5m from the obstacle.

The speed of sound can be calculated using Equation (3), which is closely related to the medium temperature (Brooks & White, 2022).

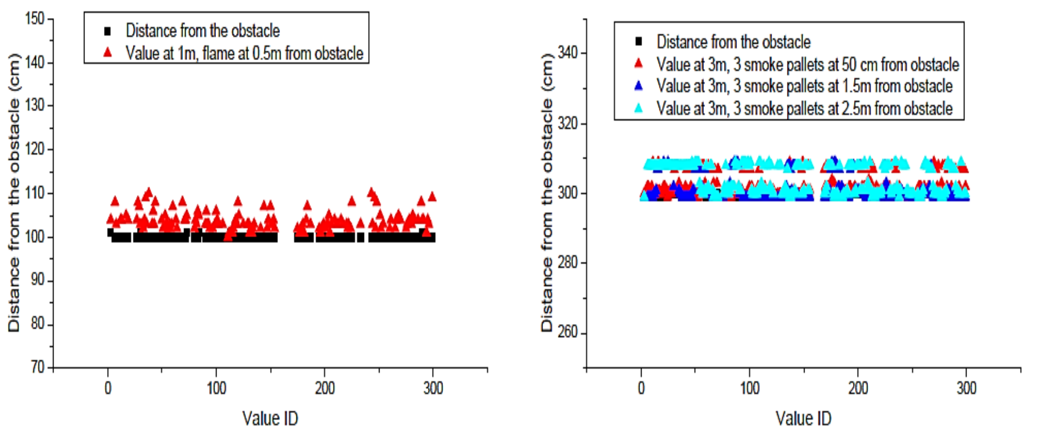
$$v = \sqrt{\frac{\gamma RT}{M}} = \sqrt{\frac{(293K)\gamma R}{M}} . \sqrt{\frac{T}{293K}} \tag{3}$$

Where γ is the adiabatic index, $R = 8.31\, J/mol.K$ is the gas constant, T is the absolute temperature in kelvins, and M is the molecular mass. For example, in the case of air $\gamma = 1.4, M = 0.02897\ kg/mol$, if the temperature T=20 °C (T=293K), the speed of sound is v = 343 m/s, so the equation of sound speed can be simplified as:

$$v = 343\sqrt{\frac{T}{293K}}\, m/s \tag{4}$$

Therefore, the sound speeds in different mediums are: 354.5 m/s in smoke, 656.4 m/s in propanol, and 625 m/s in kerosene. Assume that the field of high temperature caused by fire or smoke is evenly distributed and the width of the field equals to the fuel pan, e.g., 0.1 m for a fuel pan with a diameter of 0.1 m. Ultrasonic distance sensor works based on the measurement of distance that sound travels, which equals to the speed of sound in the medium multiples the time that sound travels. The default speed that the sensor adopted is 343 m/s, and the measured distance is 0.95 m when the nominal value is 1 m. The measured distance by sensor is smaller than the original distance. And the measured distance should be independent of the fire location and closely related with the type and size of fire.

Figure 8: Sonar values using simple filtering



(a) Filtered Sonar value at 1m, smokeless flame at 0.5m from obstacle.

(b) Filtered Sonar value at 3m, flame at 0.5m, 1m, 1.5, 2 and 2.5m from obstacle.

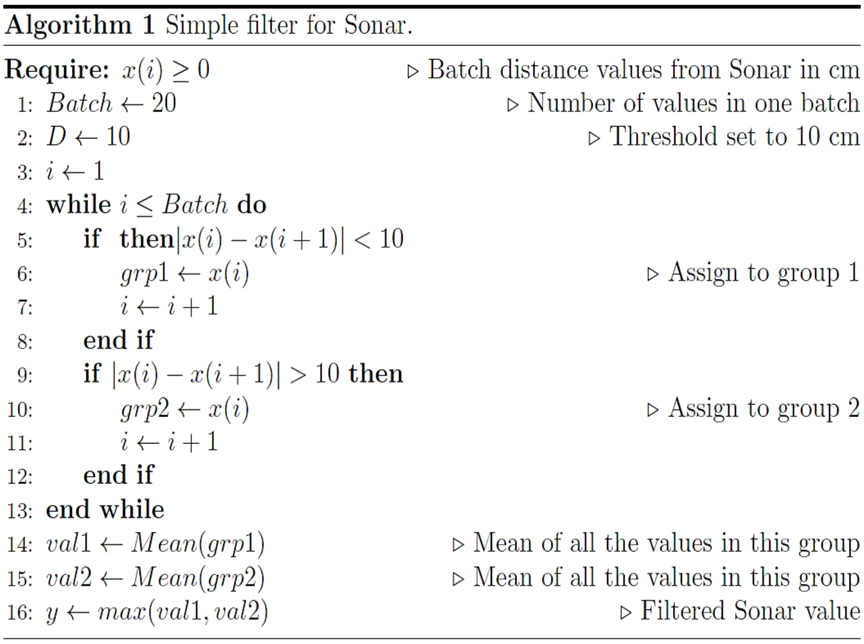
3.5. Simple filtering algorithm

A simple filtering algorithm has been developed to use Sonar values affected by fire and smoke environment interference. The goal of this algorithm is to filter out unwanted readings from Sonar. Algorithm 1 requires distance values from Sonar in batches. One batch of values can contain any number of values. Batch size will decide the time the algorithm takes to output a filtered value. If Sonar is set to operate at 100Hz and with a batch size of 20, Sonar can output 5 filtered values each second. The proposed algorithm also requires an accuracy threshold value, for our purpose we can set accuracy threshold as 10 cm. Each value in the batch is compared with the next value and the corresponding difference is calculated. If the difference is less than the threshold, the value is placed in group 1. Otherwise, it is placed in group 2. The mean of both groups is calculated, and the maximum of the mean values is selected as a filtered value.

Results show that the proposed filtering algorithm is successful in providing satisfactory output. It is not only successful when applied to Sonar values affected by flame interference, but it also improves the result when applied to smoke affected values. We know that Sonar is relatively unaffected even by high density smoke as shown in Figure 6c, but simple filtering improves it further as shown in Figure 8b. The standard deviation is also slightly improved as shown in the last row of Table-1. The major advantage of the proposed algorithm can be seen in the case of flame interference.

After discarding unwanted values, relatively accurate results can be achieved as shown in Figure 8a. Standard deviation is also improved as compared to the standard deviation of unfiltered data (please see row 4 of Table-1). It can be observed that after filtering out unwanted values, Sonar can output relatively accurate distance of obstacle. However, this output depends upon the value of threshold set in the algorithm. Higher value of threshold will increase the number of data points but decrease the accuracy of Sonar output while lower value of threshold will increase the accuracy of Sonar output but decrease the number of data points leaving gaps in the output value. The proposed filtering algorithm minimises sonar result when interference is only smoke because Sonar is already quite accurate near flameless smoke. Slight improvement in results due to filtering can be observed in Figure 8b when compared to Figure 6c. The standard deviations for filtered sonar values in smoke are shown in row 5 of Table-1, almost the same as the standard deviations of unfiltered sonar values listed in row 3.

Figure 9: Proposed filtering algorithm of the study



Algorithm 1 Simple filter for Sonar.

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Require: $x(i) \geq 0$                      ▷ Batch distance values from Sonar in cm
$Batch \leftarrow 20$                       ▷ Number of values in one batch
$D \leftarrow 10$                           ▷ Threshold set to 10 cm
$i \leftarrow 1$
while $i \leq Batch$ do
    if then$|x(i) - x(i+1)| < 10$
        $grp1 \leftarrow x(i)$              ▷ Assign to group 1
        $i \leftarrow i + 1$
    end if
    if $|x(i) - x(i+1)| > 10$ then
        $grp2 \leftarrow x(i)$              ▷ Assign to group 2
        $i \leftarrow i + 1$
    end if
end while
$val1 \leftarrow Mean(grp1)$                ▷ Mean of all the values in this group
$val2 \leftarrow Mean(grp2)$                ▷ Mean of all the values in this group
$y \leftarrow max(val1, val2)$              ▷ Filtered Sonar value
```

4. Conclusion

Low visibility in a fire and smoke environment can cause many hindrances, such as decreased firefighters' capability or injuries leading to loss of life. Distance sensors mounted on assistant robots or firefighters can be helpful in navigation, mapping, or obstacle detection. However, these sensors can lose effectiveness in a fire and smoke environment. This paper investigates the efficacy of widely used ultrasonic distance sensors. Fire and smoke environment is simulated using smoke pellets to generate flameless smoke, 2-Propanol to generate smokeless flame, kerosene to simulate high-temperature flame with black smoke, and 2-Propanol with smoke pellets to generate high-temperature flame with heavy smoke. Sonar operates under the influence of these interferences, and empirical data is collected. Aspects of Sonar operation under fire and smoke conditions are discussed in detail.

Experiments are conducted to assess the capability of Sonar when it is near smoke, flame and flame with smoke. Results are discussed in detail, and the breaking point of Sonar's operation capability is identified. The effectiveness of Sonar in fire and smoke environment is also discussed. The experimental results show that Sonar is relatively effective in smoke without flame. Information can be gathered easily as long as air temperature is within a nominal range. However, the Sonar starts to behave erratically when there is a change in the medium, in this case, air. Sonar outputs mix of useful and erroneous values in the presence of flame and flame with smoke.

A simple filtering algorithm is presented to improve Sonar's result in the presence of smoke. Without filtering, Sonar outputs a mixture of accurate and erroneous values in the presence of flame. With the filtering algorithm, these unwanted values can be discarded, and useful information can be retrieved. Results show that using filtering, Sonar is a good candidate as a distance or range finder sensor in a fire and smoke environment. In the future, the effectiveness of the proposed methodology in real-time smoke and fire detection can be explored. A similar methodology and experimental setup can be used to evaluate other distance sensors like LIDARs and cameras. It will be useful to see how different distance sensors act in fire and smoke environments. A comparative analysis can be performed to know the effectiveness of different distance sensors in varying fire and smoke environments. Techniques can be developed to use two or more distance sensors in conjunctions to obtain improved results.

Declaration of conflict of interest

The author(s) declared no potential conflicts of interest(s) with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship and/or publication of this article.

ORCID iD:

Shaheer Muhammad	https://orcid.org/0000-0003-1928-5926
Hannan Adeel	https://orcid.org/0000-0002-5348-1237
Tahir Saleem Khattak	https://orcid.org/0000-0001-7828-5382
Inamur Rehman Rao	https://orcid.org/0000-0002-9180-9758

Publisher’s Note

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