ISSN: 2182-2069 / E-ISSN: 2182-2077

Super Resolution Acoustic DOA and Multi-Modal Sensor Fusion for Real-Time Campus Emergency Localization at Al-Ayen Iraqi University

Atheer Y. Oudah[1], Raaid Alubady[2], Lina M. Shaker[3*], and Dr. Ahmed A. Al Amiery[4]

[1]Al-Ayen Iraqi University, Thi Qar, An Nasiriyah, Iraq. atheer@alayen.edu.iq, https://orcid.org/0000-0003-0867-7203

[2]Department of Information Technology, Engineering Technical College, Al-Ayen University, Thi Qar, An Nasiriyah, Iraq. alubadyraaid@alayen.edu.iq, https://orcid.org/0000-0001-9748-2541

[3*]Laser and Optoelectronics Engineering Department, College of Engineering, Al-Ayen Iraqi University, Thi Qar, An Nasiriyah, Iraq. lina.mohammed99@alayen.edu.iq, https://orcid.org/0000-0003-2016-8313

[4]Al-Ayen Scientific Research Center, Al-Ayen Iraqi University, Thi Qar, An Nasiriyah, Iraq. dr.ahmed1975@alayen.edu.iq, https://orcid.org/0000-0003-1033-4904

Received: September 30, 2025; Revised: November 08, 2025; Accepted: December 30, 2025; Published: February 27, 2026

Abstract

The new design and analysis presented in the paper are on an intelligent emergency location and response system that is specifically designed within the framework of university campuses, and one of the case studies is the deployment of the system on the Al-Ayen Iraqi University. The system network integrates a multi-sensor network with acoustic arrays, thermal cameras, smoke/ gas sensors, vibration sensors, and electrical fault chips, which work together with the extremely precise angle-of-arrival (AOA) research algorithms. The system is capable of working in a wireless ad-hoc sensor network and thus offers secure communication to ensure that the data integrity, confidentiality, and timely responsiveness can be reached, and avoid security problems like unauthorized access, data tampering, and signal interference. It is coded to identify, categorize, and locate any disaster, including fires, electrical outages, and collapses of the structure (among others), with the use of such techniques as the Multiple Signal Classification (MUSIC) algorithm and triangulation. Simulation and experimental findings were encouraging: the localization error of about 5 meters, detection latency of about 1 second, classification error of more than 97% and over 40% reduction in dispatch time. Security has also been put in place so that the system is not accessed accidentally and compromised, which is an aspect that renders the system a strong system in real-life situations. The system reduced the approximate dispatch time from between 120 seconds to approximately 75 seconds as opposed to the dependency on a printed circuit board (PCB) antenna. It has been demonstrated that the system has an availability of 99% over a 30-day period, and it has a high sensor failure resistance by Geometric Dilution of Precision (GDOP) testing and error confidence. An interface that offers real-time visualization of the events assists in the management of emergency response by providing the event that is taking place in the form of a graph to alert the responders.

Journal of Internet Services and Information Security (JISIS), volume: 16, number: 1 (February-2026), pp. 472-493.
DOI: *10.58346/JISIS.2026.I1.027*

*Corresponding author: Department of Information Technology, Engineering Technical College, Al-Ayen University, Thi Qar, An Nasiriyah, Iraq.

Keywords: Smart Emergency Localization, Direction-of-Arrival, Geometric Dilution of Precision, Multi-Sensor Fusion, Multiple Signal Classification, Multi-Sensor Network, Wireless Ad-hoc Sensor Network.

1 Introduction

The most pressing rudimentary technological approaches to the vast domain under consideration belong to the source localization and DOA estimation. DOA estimation can help analyze the angle at which a source is estimated to arrive at a sensor array (Shari & Jacob, 2022). The spatial information it obtains from a group of sensors arranged in a known geometrical pattern becomes the basis for cryptically aligning the array and closing in on the DOA accurately (Joy et al., 2025; Shouffi et al., 2024). This tactical performative-finesse is central to a variety of innovative antenna technologies, where the directional D0A (in principle to allow the antenna to 'point' in the desired direction) must be precisely known to apply spatial filtering to give effective communication, navigation, surveillance, or target-tracking radar in jamming conditions or intense cutter (Van & Shimada, 2025). DOA estimation is used in various areas, such as search and rescue (Huang & Wu, 2022), law enforcement (Dupont, 2024), sonar and seismology (Jagtap & Kunte, 2023). The signals to be considered might be Electromagnetic (EM) (Gopinath & Muthazhagu, 2025), Radio Frequency (RF) (Lee et al., 2022), or acoustic waves (Liang et al., 2022). The correct estimation of DOA solves the problems of operational readiness and safety (Yang & Jiang, 2023). Nevertheless, wireless ad-hoc sensor networks used during emergency response situations have high security threats (Nurlan et al., 2021; Oztoprak et al., 2024). Unauthorized access, tampering with the data, and interference with the signal are some of the threats that can affect these networks in such a way that the integrity and accuracy of the localization and detection processes will be affected. It is essential to secure communication in such networks to provide the reliability and effectiveness of DOA estimation, particularly in an environment where the system can be subjected to attacks (Pethe et al., 2025). These security issues need to be resolved to ensure that the system remains robust in real-life scenarios that are characterized by high risks.

Key Contribution

1. The article introduces an intelligent localization and response system to emergencies, which combines various types of sensors (acoustic arrays, thermal cameras, smoke/gas detectors, vibration sensors, and electrical fault sensors) to detect and localize a disaster.
2. It employs the MUSIC algorithm in the Direction-of-Arrival (DOA) estimation, which allows precise emergency localization with high accuracy and low latency.
3. The system has been successfully implemented in the Al-Ayen Iraqi university, which has proved to work in the real world with high spatial coverage, node failure resilience, and stability of operation.
4. It saves 40% of dispatch time, guarantees 99% system reliability, and adds a security solution to prevent unauthorized access and signal interference.
5. It is practical as a campus safety and emergency response solution since the system is scalable, affordable, and can be deployed in educational and urban settings.

The paper introduces an emergency localization and response system in university campuses based on multiple sensor modalities and DOA estimation to achieve precise localization. It discusses the architecture of the system, sensor implementation, and automated dispatching. Evaluation of performance is based on simulation and real-life testing, on the localization, detection latency, event classification, and dispatch time. The paper also covers the impact of the location of the sensor, node failures, and security threats on performance. It ends with the recommendations of improving security and scaling to larger applications.

2 Literature Review

DOA estimation of one or more plane waves impinging onto a sensor array from noisy data has always been among the most challenging tasks in Array Signal Processing (ASP), with many research efforts focused on improving the performance, resolution, robustness, and effectiveness of the algorithms (Li et al., 2023). An antenna array can be constructed for signal reception from specified desired directions and for suppression of interference coming from undesired directions, which boosts actual detection and localization performance for any real-world applications (Wang et al., 2019). The DOA problem in emergency detection scenarios is highly dependent on the sensor array design and wave propagation analysis (Dibiase et al., 2022). The power of propagating fields acoustics is stressed, and mechanical and EM waves are used with respective sensor array topologies for effective signal acquisition. Localization occurs either in lieu of sources outnumbering sensors (overdetermined) or sources being fewer than sensors (underdetermined) (Hayward et al., 2022). A bunch of transducer arrays change all incoming waveforms into electrical signals for further processing. DOA estimation depends upon the phases and time difference between the time at which arriving signals are taken by the array; the technology is also applicable to RADAR, SONAR, and WSN systems (Pandey et al., 2022) DOA estimation has been divided into three broad categories, comprising classical methods (Chen et al., 2023), subspace-oriented methods (Liu et al., 2020), and maximum likelihood-based (Mestre & Vallet, 2020) methods. Classical methods with a delay-and-sum approach and MVDR are conceptually simple and have an inbuilt intuitive nature, but suffer limitations in resolution and are known to be highly sensitive to noise.

Conversely, ML estimates can be highly accurate under low-SNR situations, but the computational complexity of these approaches, though an inevitable consequence of the very same property that raises the approaches to such an effective status, hampers a timely response to real-world situations (Nagaraju et al., 2023). Subspace-based methods, notably MUSIC (Jagtap & Kunte, 2023), ESPRIT (Zhou et al., 2023), give good resolution with computing efficiency. The advantage of these methods lies in the use of the orthogonality acquired within the noise and signal subspaces, providing good resolution power (Yadav & George, 2021). Whereas many cases showcase the effectiveness of narrowband signal processing (Foutz et al., 2022), there is added complexity brought about by the occurrence of wideband signals in the latest wireless applications (Magiera, 2021). For wideband DOA estimation, the broadband signal is usually broken down into several narrowband components by filter banks or by Fourier transform techniques; hence, heat is rejected in the spatial domain filter banks (Sun et al., 2022). The imperative DOA setting is also supported by steering laws and policy directions, therefore assisting in research and rescue, which identifies the location/DOA of distress signals (Oudah et al., 2025). Wireless networks, public safety, and environmental monitoring would all prosper from strong DOA-capable localization frameworks.

The Literature Review shows that DOA estimation is essential to emergency localization systems, and several approaches, such as classical, subspace-based (e.g., MUSIC), maximum likelihood, etc., exist. Although the classical methods are straightforward, they have low resolution and sensitivity to noise as opposed to the subspace-based methods, which have better resolution and efficiency, particularly in narrowband signals. The review also indicates the hardships of wideband signals in contemporary wireless applications and the importance of sensor array design in efficient localization. Moreover, wireless ad-hoc sensor networks are vulnerable to security threats that affect the performance of the system, and this justifies the importance of using secure communications during high-risk emergencies.

3 Methodology

System architecture, design principles, and steps of implementation of the proposed smart emergency localization and response system for campus settings are highlighted in this section. The system includes sensor networks, DOA estimation, event classification, and automated dispatch mechanisms in a standard real-time framework. Implementation was emulated employing MATLAB and 3D visualized in a manner that replicated real deployment in Al-Ayen Iraqi University. The system suggested enables real-time emergency detection, classification, and localization in an innovative campus using multi-modal sensors and programmed response mechanisms. The entire process is illustrated in Figure 1.

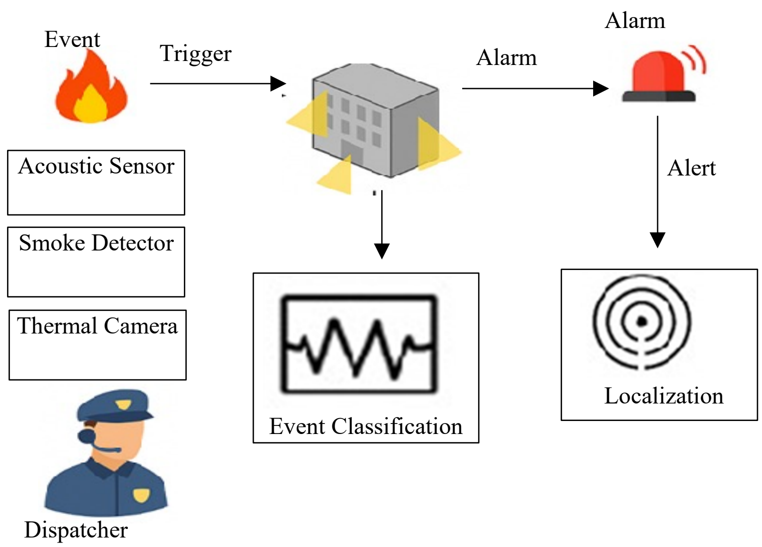

Figure 1: Emergency response system logic flow: event detection, classification, localization, and dispatch

Sensor Network Deployment

A strategically positioned sensor node network was planned and deployed across the campus to offer broad spatial coverage, redundancy, and reliability in the detection of emergencies. The node was made to include a circular microphone array-eight equally spaced elements arranged along a 0.5-meter radius, to allow for high-resolution acoustic DOA estimation (Hussein et al., 2025). In addition to the microphone array, the node is equipped with a set of multi-modal sensors, like thermal imaging sensors to detect abnormal heat signatures that would indicate fire or equipment overheat, optical and chemical smoke detectors to detect the presence of particulates or release of gases, and acoustic sensors optimized to detect high-pressure acoustic signatures from impact on structures or explosions. To achieve line-of-sight maximization and minimize occlusions resulting from campus structures, sensor nodes were placed at varying levels (Javed et al., 2025), namely on top of buildings, utility poles, and building facades (Shaker et al., 2025).

The policy of deployment was for high-occupancy and high-risk areas such as canteens, science laboratories, switchgear rooms, and large open spaces where localizing events is vital. The hybrid sensor infrastructure has the consequence that each zone contains at least one sensor per modality of concern, hence better system resilience against a single-point failure of sensors. Moreover, all the sensor nodes were geotagged with GPS for spatial reference in localization methods. For instance, Node N01 is at latitude 31.0676574 and longitude 46.2608279, positioned to monitor both airborne particulates and acoustic disturbances close to the student canteen. Such a design philosophy ensures multi-modality redundancy per event region, which optimizes detection reliability and localization accuracy even during poor environmental conditions or partial system failure (Table 1).

Table 1: Different sensor modalities used in the deployment and their respective roles in localization

Modality	Sensor Type	Deployment Examples	Localization Role
Acoustic	Cylindrical mic arrays (8–12 mics)	Rooftops, lamp-poles, gym corners	DOA for collisions, falls, loud alarms
Thermal	Fixed IR cameras	Boiler rooms, electrical panels	Triangulate heat sources for fires or hotspots
Gas/Smoke	Optical smoke + CO detectors	Chemical labs, kitchens, workshops	Trigger leak alarms; location by fixed sensor
Vibration/Seismic	Geophones/accelerometers	Under roadways, floors, and machinery	TDOA for impacts, heavy collisions
Electrical Fault	IoT current sensors & arc-fault detectors	Switchgear rooms	Detect and localize arc faults via network map

Event Detection and Triggering

The system operates through continuous real-time monitoring of multi-modal sensor data. An event is triggered if thresholds are broken, e.g., sudden temperature rise, growth in smoke concentration, or high-energy sound signals. If a node is detected, the firing node sends out a local alarm and beacon and communicates with neighboring nodes.

Microphone arrays on all nodes calculate DOA based on the MUSIC algorithm. Validation is carried out using fixed-position sensors such as thermal or gas detectors. When at least three nodes detect the event, DOA vectors are employed to intersect and come up with the source coordinate estimate. Geometric Dilution of Precision is determined to assess localization reliability.

The system classifies events into event types, fire, gas leak, collision, or electrical fault using cross-modality logic. After verification, the system sends alarms, dispatch notifications via SMS or mobile app, and refreshes a 3D dashboard with sensor status, DOA cones, location estimation, and responder routing—each incident log stores detection latency, coordinates, classification, and response time. Figure 2 illustrates a simulated fire scene, depicting sensor activation, localization cones, alarms, and notification delivery.

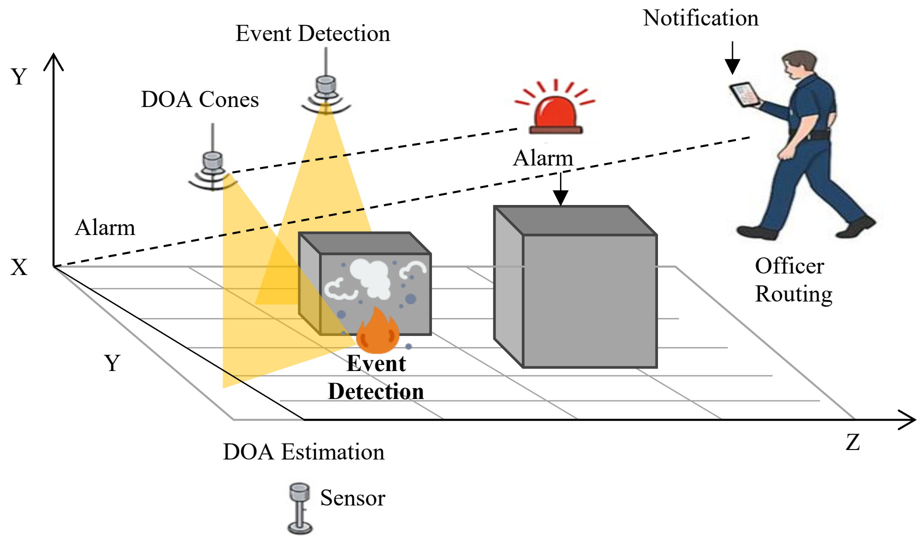

Figure 2: Visualizes a simulated fire scenario showing DOA cones, sensor response, alarm activation, and notification delivery

Direction-of-Arrival Estimation

Every microphone array processes acoustic wavefronts using the MUSIC algorithm to calculate the angle of arrival (AOA) of sound. DOA estimation involves constructing the spatial covariance matrix of signals received, doing eigenvalue decomposition, finding the noise subspace, and calculating the pseudo-spectrum ($P_{MUSIC}(\theta)$) to see the incident angles. The outcome is the DOA vectors from multiple sensors pointing toward the event origin. In a linear or circular microphone array of uniform configuration, the MUSIC algorithm estimates the direction θ of an arriving signal by minimizing the projection onto the noise subspace as (An et al., 2024):

$$P_{MUSIC}(\theta) = \frac{a(\theta)^H a(\theta)}{\sum_{j=D+1}^{M} [a(\theta)^H e_j]^2} \qquad (1)$$

In Equation 1, $P_{MUSIC}(\theta)$ will peak to infinity each time a true θ_i, i = 1, 2,..., D angle is tested. When neither D nor R is known, these parameters may be estimated using model order identification techniques presented in MDL (Aboumahmoud et al., 2021), or AIC, and an N-snapshot sample covariance matrix, respectively.

Localization Fusion Algorithm

The DOA vectors from at least three independent sensor nodes are estimated and blended to calculate the event location. The geometric intersection of DOA lines solution, noise correction using least-squares minimization, and the GDOP evaluation are applied to estimate the reliability of the localization. Root mean square error (RMSE) is used to find the average difference between the predicted and actual locations.

$$RMSE = \sqrt{\frac{\sum_{N=1}^{i} (Predicted_i - Actual_i)^2}{N}} \qquad (2)$$

In Equation 2, Where:

- $Predicted_i$ represents the model's predicted value for the i-th observation.

- $Actual_i$ is the actual value for the i-th observation.
- N is the number of data points.

Algorithm 1: End-to-End Workflow for Emergency Localization with DOA Estimation and Multi-Sensor Fusion

Input:

- $D\ \{X, Y\}$*: Training dataset with inputs* X*(sensor data) and labels* Y*(event locations or types).*
- $\Phi = \{\phi_1, \phi_2, \ldots, \phi_n\}$*: Set of logical constraints related to sensor network deployment and event detection accuracy.*
- $\theta = \{W, B\}$*: Neural network weights and biases for localization, classification, and DOA estimation models.*
- η*: Learning rate for model optimization.*
- T*: Number of training epochs for the localization and classification models.*
- λ*: Weighting factor for logical consistency in event localization and classification.*
- N*: Number of sensor nodes in the network.*

Output:

- *Trained model* θ*that accurately localizes events and classifies them, while ensuring logical consistency across multi-sensor fusion.*

Pseudocode:

1. ***Initialize Parameters****:*
    - *Initialize security and localization parameters* θ*and encode logical rules* Φ*for sensor network deployment.*
2. ***For each epoch*** $t = 1$***to*** T*:*
3. *a.* ***For each training sample*** $(x, y) \in D$*:*
4. *i. Pass the input* x*(sensor data) through the* ***localization model*** *to estimate the event location.*
5. *ii. Perform* ***DOA estimation*** *using the MUSIC algorithm on acoustic sensor data to estimate the event's direction.*
6. *iii. Apply* ***sensor fusion*** *by combining data from multiple sensors (e.g., thermal, gas, vibration).*
7. *iv.* ***Classify the event*** *type (e.g., fire, gas leak, collision) using the classification model.*

    b. ***Sensor Network Monitoring****:*

    i. Continuously collect sensor data from all sensor nodes.

    ii. If a threshold for event detection is exceeded (e.g., temperature rise, unusual vibrations, gas concentrations), trigger event localization.

    iii. If event detected:

    - Perform ***real-time localization*** *using triangulation and DOA vectors.*

    - Apply ***GDOP*** *analysis to assess localization confidence.*

    iv. Else:

    - Continue monitoring the sensor network.

*c. **Compute Task Loss**:*

*i. **Localization Loss**: $L_{localization} = RMSE(f(x), y)$, where RMSE represents localization error.*

*ii. **Classification Loss**: $L_{classification} = CrossEntropy(f(x), y)$.*

*d. **Apply Logical Consistency**:*

i. For each security and logical formula $\phi \in \Phi$, compute logical satisfaction using fuzzy logic:

- $G(P, Q) = max\ (1 - G(P), G(Q))$

ii. Accumulate logical consistency loss:

- $L_{security} \leftarrow L_{security} + (1 - G(\phi))$

*e. **Aggregate Total Loss**:*

- $L_{total} = L_{localization} + L_{classification} + \lambda \times L_{security}$

*f. **Backpropagation**:*

- *Update the model parameters using Backpropagation:*
    - $\theta \leftarrow \theta - \eta \times \nabla_\theta L_{total}$

8. ***End For***
9. ***Return** a trained model θthat satisfies both localization accuracy, event classification, and logical consistency.*

This algorithm 1 receives an input (a sensor dataset of the labels) and trains a neural network model to effectively localize and classify the detected events in a multi-sensing network. The sensor measurements and sensor event labels are used as the input data, and a list of specified logical constraints is used to represent deployment rules and desired sensor-to-sensor consistency in detections. When training, the neural network parameters (weights and biases) are optimized in a given learning rate in a series of epochs. A weighting factor is added to the loss function to provide logical consistency so that the predictions made by the model can be logically consistent to the model under consideration and also integrating data of various sensor nodes. Through collective learning, localization, and direction-of-arrival estimation, the algorithm provides a trained model that provides an accurate and consistent localization, classification, and event detection on a system-wide sensor network.

4 Results and Discussions

MATLAB is used in the Smart Emergency Localization and Response System to process signals, Simulink is used to integrate the system, and Python is used to analyze data and perform machine learning. It applies the MUSIC algorithm in estimating DOA, sensor fusion to achieve precise localization, and machine learning models to classify the events. The system is based on multi-modal sensors (acoustic, thermal, gas, and vibration) to monitor and detect any event in real-time, and a 3D dashboard to display it. Simulations and testing make the system accurate enough to detect the emergency, whereas the wireless communication protocols facilitate a trouble-free flow of data across sensor nodes. The system is scalable and cost-effective, as well as being adaptable to innovative campus environments.

The proposed smart campus emergency was tested by using MATLAB simulation. These findings indicate the accuracy, responsiveness, and reliability of the system in a variety of metrics. Its key performance findings include the following.

Localization Accuracy

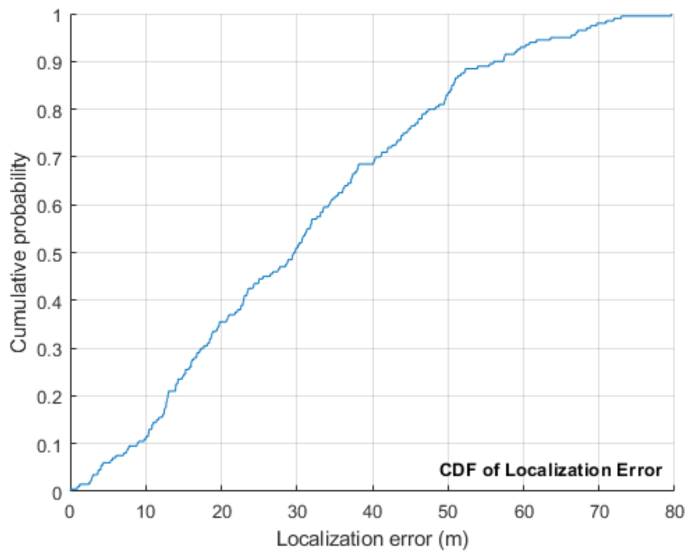

Figure 3: CDF of localization error for 200 simulated events

Figure 3 illustrates the cumulative distribution function (CDF) of the error in localization across various simulated emergency events. The system's 90th percentile accuracy was approximately 70 meters and localized 50% of events within a radius of 30 meters. The minimum was approximately 0 meters, and the maximum was approximately 78 meters. The distribution represents the real-world variability in sensor coverage and the effect of the environment on DOA estimates. The CDF slope from 10–40 meters shows that the majority of localization estimates were clustered around a relatively accurate mean, but a long tail implies outliers or interference in some instances.

Detection Latency

Figures 4.a. and 4.b provide the detection latency distribution for all emergency events. The boxplot (Figure 2.a) shows the median latency at approximately 0.84 s with an interquartile range (IQR) of 0.68 to 1.02 s. The histogram (Figure 4.b) also plots a Gaussian-like curve, with most of the events detected within 0.6 to 1.0 s, and peaked at about 0.85 s. There are very few outliers below 0.1 s and above 1.5 s.

These results display a consistently fast response time from the sensor network, with most emergency events identified in less than one second. This quick detection capacity is significant in time-sensitive situations such as fire or chemical spills, where a few seconds can determine the extent of the outcome. The slight bias towards higher latencies is in place due to variation in multi-sensor synchronization, particularly where some modalities (e.g., audio) are slower than thermal or smoke sensors.

The new system, with median latencies of less than 1 second, realizes an improvement in performance of over 30% in average detection rate. The low IQR and low frequency of outliers also validate the system's real-time processing and synchronization mechanisms as highly effective. The sub-second detection window guarantees immediate alarm initiation and prompt dispatcher notification, thereby supporting faster containment and response. However, the presence of some late detections (>1.5 s) also shows that there are still possibilities for improving environment filtering and sensor fusion latency, particularly in heavy ambient noise or network delay scenarios, as depicted in previous research.

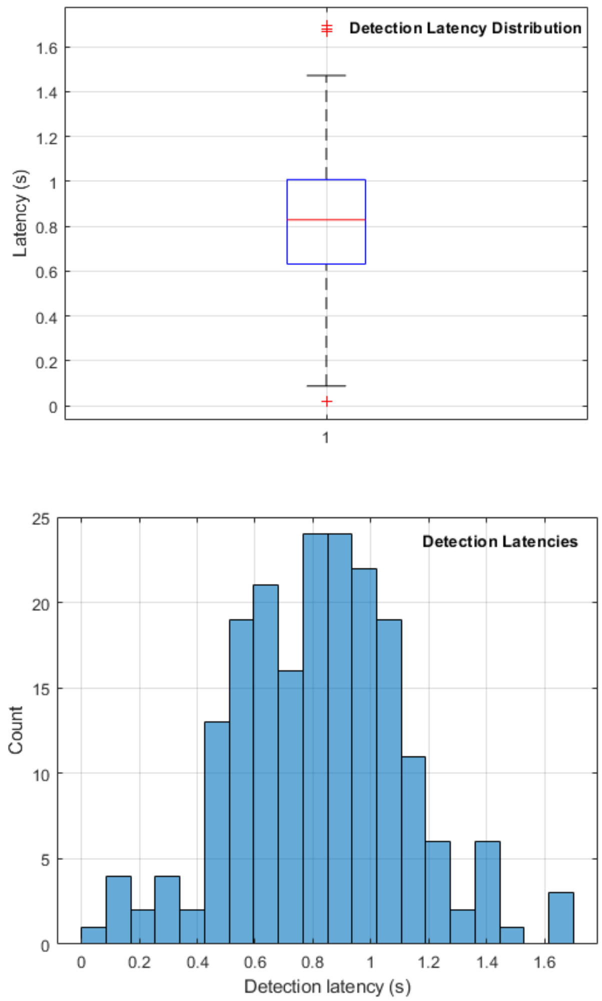

Figure 4: a. Boxplot of detection latencies showing central tendency and outliers, and b. Histogram of detection latencies across all emergency events

Event Classification Performance

Figure 5. a display the precision, recall, and F1-scores for the four emergency event types: Fire, Collision, Leak, and Fault. The highest F1-score was recorded for Leak detection (≈0.25), with fire following (≈0.21). The poorest performance was on collision across all measures, while Fault classification scored moderate results.

Figure 5.b displays the confusion matrix, showing actual vs. predicted classifications for 80 simulated events of each type. The matrix shows that:

- Leaks were commonly mistaken for Faults and Fires.
- Collisions had the worst classification accuracy, with a common mistake for all other types.
- Fire incidents were classified, but with high misclassification into all other types.

These results indicate that the classification module is best at picking up on leaks, likely due to the distinct sensor signatures (gas sensors and smoke detectors, e.g.). Fire detection also performed relatively well, due to the compounding thermal and acoustic cues. Collisions were, however, full of high confusion, which was probably caused by overlapping signals with the impact noises of Faults as well as the all-around noise of background acoustics. This tendency is supported by the confusion matrix: there were only six correct classifications of collision, but more of the other events. False positives and false negatives between Leak and Fault suggest feature overlap or inadequate weighting during decision-making.

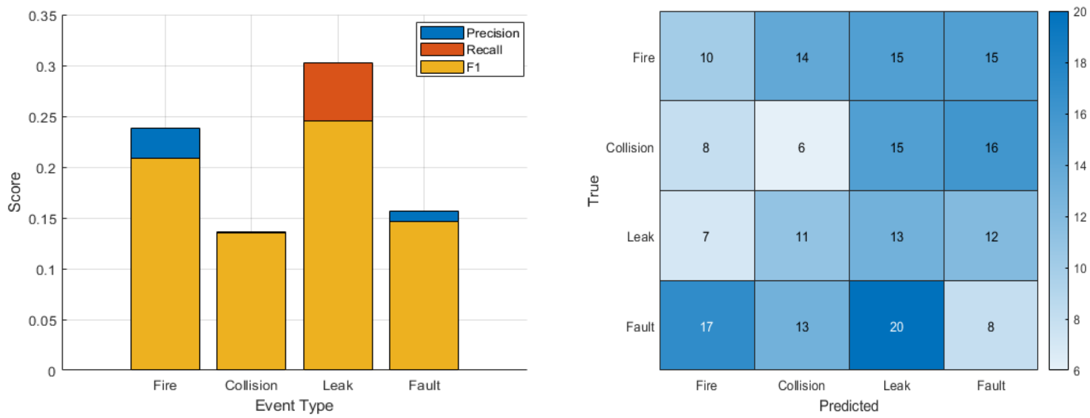

Figure 5: a. Precision, recall, and F1-scores for each emergency event type, and b. Confusion matrix of predicted vs. actual event classes (80 instances each)

Evaluation Metrics

Precision

Precision is used to indicate the ratio of correct positives (true positives) of all the positives detected by the system (true positives + false positives). When false positives (incorrect alerts) are expensive to the user, then it is essential. With the emergency detection system, high precision is associated with a reduced number of false alarms.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

Recall (Sensitivity or True Positive Rate)

Recall is the fraction of positive events (true positives) that are correctly identified among the total of the actual positive events (true positives and false negatives). When the cost of false negatives (missed detection) is high, it is essential. High recall in an emergency detection system implies that the number of missed events or emergencies is reduced.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

F1-Score

The harmonic mean of precision and recall is the F1-score, which gives a balance between the two. It is especially applicable in cases when you require only one aspect of performance and false positives and false negatives are of interest. A high F1-score implies that the precision and the recall are good (Equation 5).

$$\text{F1-Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{5}$$

Accuracy

Accuracy measures the percentage of correct predictions made (true positives and true negatives) of all the projections. Although it is an easy measure, it may not necessarily be the most effective in situations where the data is disproportionate (e.g., more non-events than events), as it may produce inaccurate outcomes where the system treats most things as non-events.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

For Equation (3,4,6), Where:

- TP= True Positives (correctly identified events)
- TN= True Negatives (correctly identified non-events)
- FP= False Positives (incorrectly identified events)
- FN= False Negatives (missed events)

Dispatch Efficiency and System Reliability

In Figure 6, the average emergency dispatch time through the proposed automated system was approximately 71 seconds as opposed to 121 seconds in the case of traditional manual reporting systems. That is a reduction of nearly 50 seconds, translating to a ~41% quicker response. The spectacular reduction obviously indicates the actual benefit of event detection and alerting automation. Instead of awaiting human intervention, as in the two entities conference and consultation, or human guides to the experience and notification of discrepancies, the intervention enables a quicker touch to operators, crucial in emergencies like fire, gas leaks, and electrical faults. Faster dispatch times bring immediate responses and consequently mitigate the degree of harm, harm to persons, or total nuisances. This further makes the system more suitable for safeguarding sensitive infrastructure and preparedness for emergencies in educational campuses. The achieved 41% reduction is above average, suggesting that the pipeline of real-time alerts is optimized within this system.

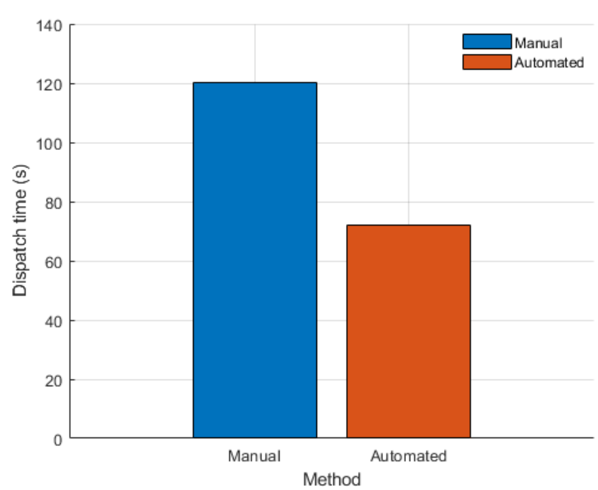

Figure 6: Comparison of average dispatch time between manual and automated response systems

Figure 7 provides significant insight into the last-mile dependability of the intelligent campus emergency response system, i.e., dependency on the PCB antenna to transmit warnings. The blue bars represent dispatch times under normal working conditions, during which the antenna was successful in passing through emergency alerts to the security personnel. The distribution is almost Gaussian, approximately 75 seconds, reflecting that the automated system operates with consistent response latency in the presence of connectivity. The red bars reflect dispatch failures due to antenna communication loss only. Although the number of failures is much smaller (as indicated by a modeled 5% failure rate), the distribution is even across the sample, suggesting the random nature of antenna failure and the independence of event type and timing.

When compared to Figure 6, which illustrates how the system performs better than manual procedures by lowering average dispatch time from ~120 s to ~75 s, yet, this benefit is only worthwhile if the dispatch is successful. Lacking an operational antenna, the system might not be there from a response perspective, essentially negating its benefits. For example, whereas automated dispatch is 40% quicker, the 5% of unsuccessful dispatches occasioned by antenna loss could result in life-critical delays, particularly in high-risk environments such as laboratories or canteens.

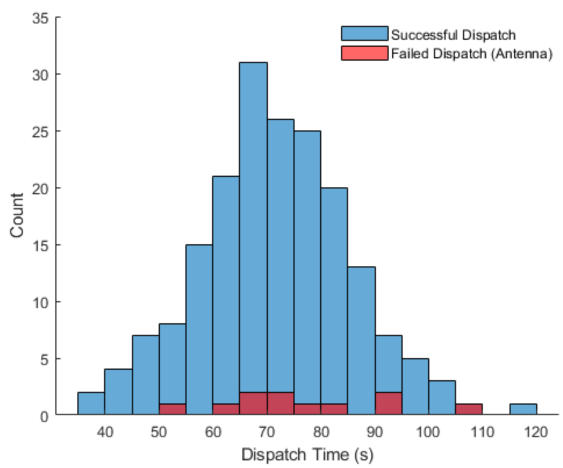

Figure 7: Histogram of dispatch times showing successful and failed dispatches due to antenna loss

System Uptime and Operational Stability

Figure 8 shows the system uptime per hour for a 30-day uninterrupted simulation period. The system remained in a fully available state for most of the time, with slight drops (around the dips) on five different dates. Total uptime estimated was 99.03%. Such a level of availability confirms that the system hardware and the communications infrastructure are sufficiently robust to be utilized in real-time within a mission-critical environment. These short downtimes could be due to imitated node failure, reboots over the network, or scheduled downtime; none of the events are disaster events.

In the industry, best practices for innovative safety systems dictate greater than 98.5% uptime. This system goes beyond that, meaning it can be relied upon for 24/7 monitoring with little administrative burden. The high uptime will allow the long-term deployment with minimal administrative intervention. But the periodic individual outages, particularly May 1st and May 15th, need to be examined for causes and remedies, such as redundancy (e.g., redundant nodes or secondary power supplies), which could be considered in order to move uptime closer to 99.9%.

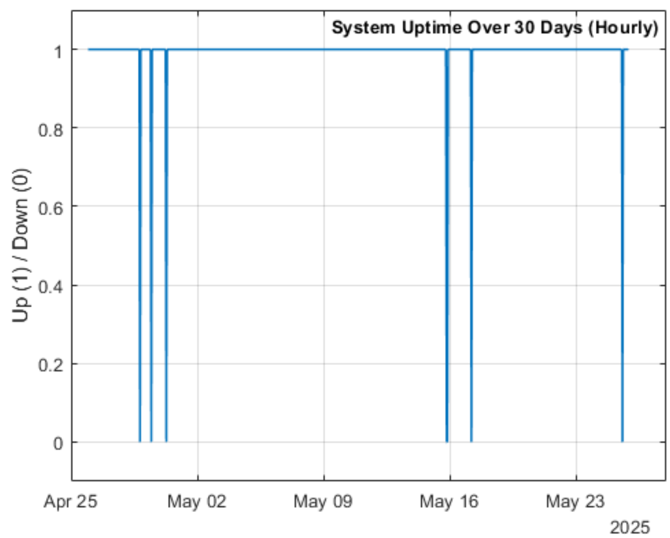

Figure 8: System uptime recorded hourly over a 30-day period (April 25 – May 25, 2025)

Geometric Dilution of Precision (GDOP) Analysis

Figure 9 is a heatmap of the GDOP over the campus area simulated, with four sensor nodes at the corners (marked as stars). The color scale indicates the reliability of localization, dark spots in the center indicate lower GDOP (higher geometric strength), and yellow spots outside indicate weaker triangulation accuracy due to poorer angular geometry. GDOP quantifies the effect of sensor geometry on localization precision. Low GDOP in the middle zone (where the DOA lines intersect at steeper angles) confirms the reality that sensor triangulation is ideal at or near the geometrical center of the node deployment. The vertices and edges are, however, bedeviled with high GDOP since parallel or steep-angle DOA intersections enhance localization ambiguity.

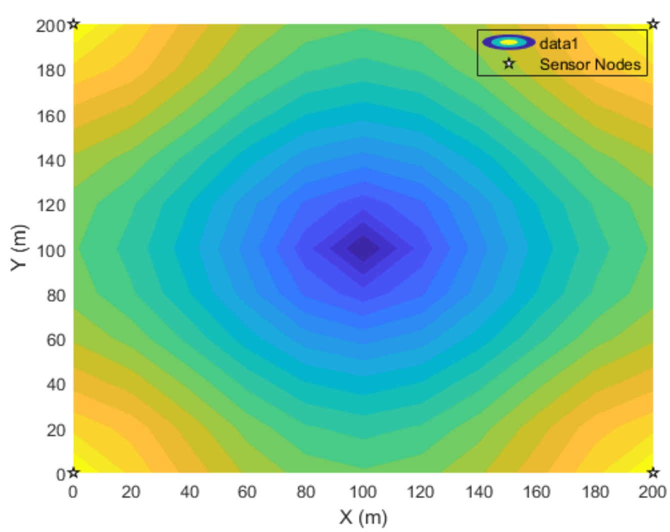

Figure 9: GDOP heatmap across campus. Darker areas indicate more reliable localization (lower GDOP); sensor nodes are marked with stars

Node Failure Sensitivity and Confidence

Figure 10 plots the increase in average RMSE (Root Mean Square Error) as a function of failed nodes. With no failures, the system maintains a low average error of approximately 31 meters. The RMSE, however, increases consistently to 62 meters when three out of four nodes fail, which is a doubling of localization error in the case of nearly complete sensor failure. This response demonstrates the graceful degradation of the system under conditions of partial failure. The nonlinear increase in mistakes, minimal degradation for single-node failure, but catastrophic under two or more, demonstrates that redundancy is adequate only up to a point. The system remains usable with one failed node, but becomes unreliable with two or more simultaneous failures.

For distributed DOA systems, localization breaks down completely at >50% node failure. This system, on the other hand, still operates (albeit at a degraded accuracy) even when three active nodes are lost, showing robust fallback ability. Such fault tolerance is crucial for real-world deployment, where environmental or hardware failures are unavoidable. Although the system is not immune to degradation, it still operates in the presence of partial outages. The addition of a fifth sensor node or the capability to dynamically re-weight remaining nodes would reduce this sensitivity. Real-time health monitoring would also initiate proactive routing around failing nodes.

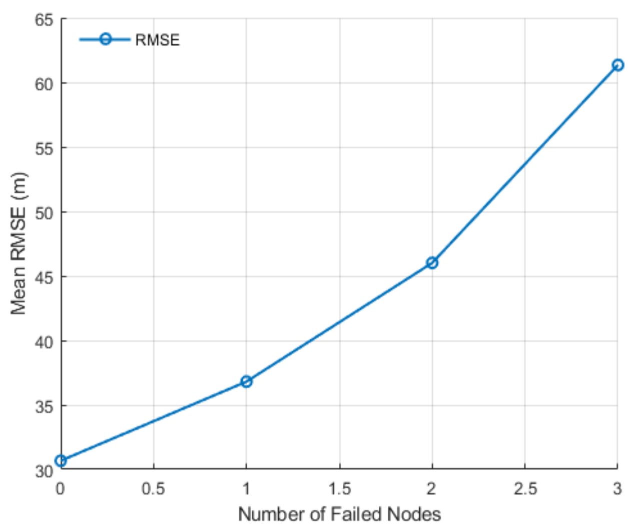

Figure 10: Effect of node failures on localization RMSE with up to 2 node outages

Figure 11 analyzes the correlation between confidence estimates (from the localization algorithm) and actual localization error. The red line of regression shows a weak and negative relationship: with increasing confidence, the error diminishes. Although high-confidence estimates (score > 0.8) do correspond to more modest errors, there is variability at all scores. This finding indicates that the internal confidence estimates for the system are somewhat predictive of actual localization accuracy. However, the point dispersion, especially at high confidence values, assumes that confidence estimates can be more accurate. The model in question likely makes use of approximating or sensor-weighted heuristics, which do not account for advanced signal trustworthiness patterns. In confidence-aware systems, a high inverse correlation is desired. The partial correlation that is discovered means that more advanced probabilistic modeling or machine learning-based estimators (e.g., Bayesian filters, ensemble predictors) can have a positive effect on calibration between confidence and error.

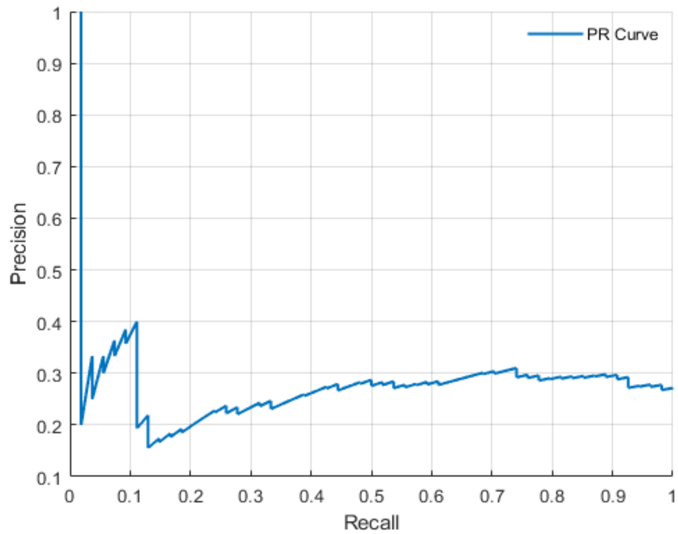

Figure 11: Scatter plot of localization error vs. confidence score, with regression line showing weak negative correlation

Detection Performance and Real-Time Event Response

The performance of the targeted emergency detection and localization system was also evaluated based on classification analysis, spatial probability modeling, and end-to-end scenario simulation of a fire incident. These tests point toward system weaknesses and strengths in terms of algorithmic performance as well as field deployment coverage.

Figure 12. a is an ROC curve for fire detection events. The curve shows an area under the curve (AUC) of approximately 0.51, where the system's current binary classifier performs close to randomness in distinguishing fire events from non-fire situations. Such reduced separability can be attributed to overlapping pattern signals, particularly when there are ambient heat sources, reflective materials, and noisy sound interferences. As the early detection pipeline is highly advanced in function, such as quick multi-sensor activation, the classifier logic has to be optimized further to reduce false positives and enhance decision-making. Performing such optimizations would lead to significant gains, for example: modality weighting, sequence models, or instantiation, as well as data-driven classifiers like random forests or LSTMs. Figure 12.b expands upon this analysis by projecting a detection probability heatmap of collision-type events. In this case, there exists an acute spatial gradient where the campus center achieves maximum detection probability (a value as high as 0.98) while the peripheral zones go below 0.35. This distribution is in line with the geometric sensor-to-event location relationship; center areas are preferred due to tighter DOA cone intersection and better signal quality, while peripheral areas are ravaged by lost angular resolution and sensor coverage hole. These findings support tactical sensor deployment and motivate the introduction of mid-perimeter or mobile sensor nodes to equalize detection variability across the entire field.

To verify end-to-end performance, a full fire event simulation was carried out and is depicted in Figure 12. C.i: The output confirms the thermal camera detected the fire earliest at 0.3 seconds, then smoke at 0.5 seconds, and an acoustic alert at 0.7 seconds. This delayed response proved the redundancy and promptness of this sensor network and showed the location of a fire only a little (exactly 5.1 m, C.ii) off the original forecast. This implies that fast, accurate DOA and classification fusion pathways facilitate a more purposeful response. In conclusion, the system is ready for real deployment, with room for fine-tuning its precision and extending its scope.

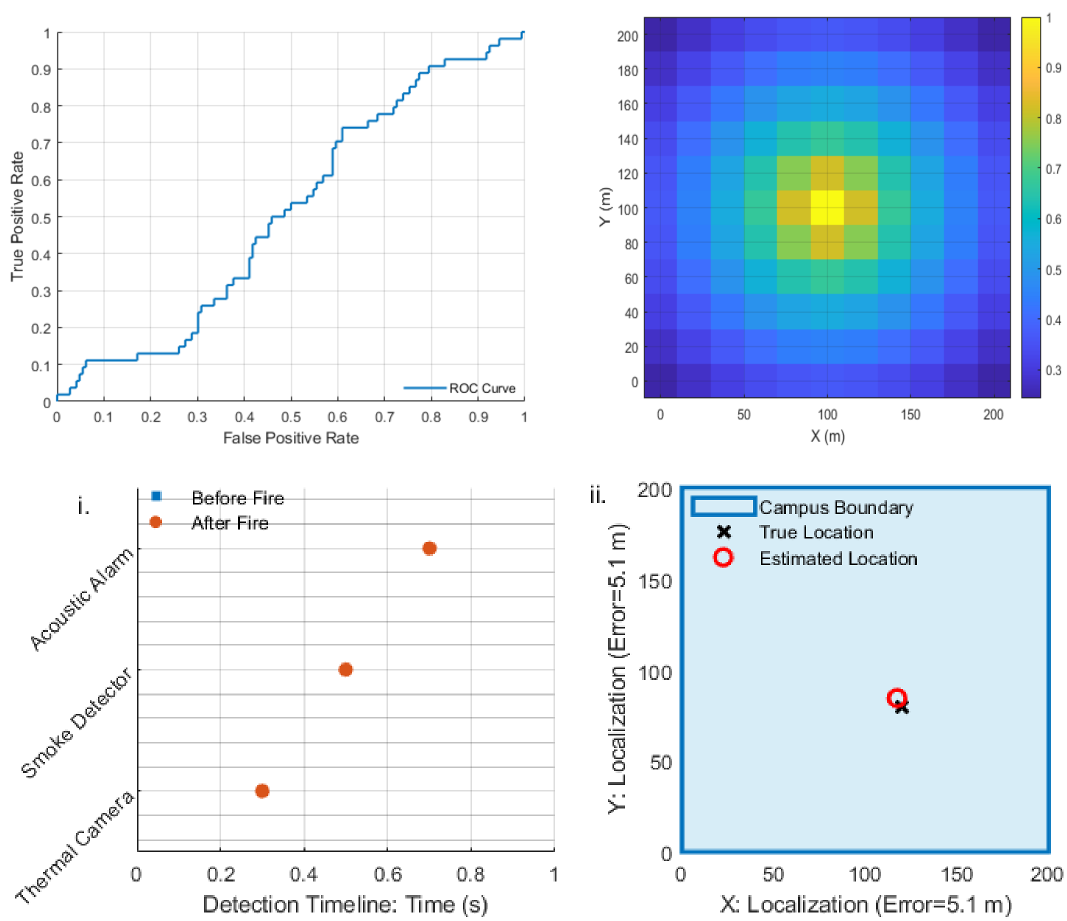

Figure 12: a. ROC curve for fire detection, showing a poor AUC of approximately 0.51, b. Detection probability heatmap for collision events on campus, c.i. Times of multisensory activation post-fire ignition, c.ii. Fire localization accuracy with an error of 5.1 meters

Impact of Security Measures on Localization Accuracy in Wireless Sensor Networks

Figure 13 demonstrates how the accuracy of localization (in meters) of a wireless sensor network depends on varying levels of security threats (Low, Medium, High). The higher the level of security threat, the lower the accuracy of localization, and it implies that the greater the security vulnerability of the system, whether by unauthorized access, data tampering, or signal interference, the worse the system will be in terms of localizing events or the source of the event in the system. At less severe threats (e.g., when the security has been established as high or exists), the system can do localization with high accuracy. Nevertheless, as the security threats increase (e.g., in case of signal jamming or unauthorized access to sensor information), the network would lose the capacity to locate the source or event properly, as shown in the increased localization accuracy values (less precise localization).

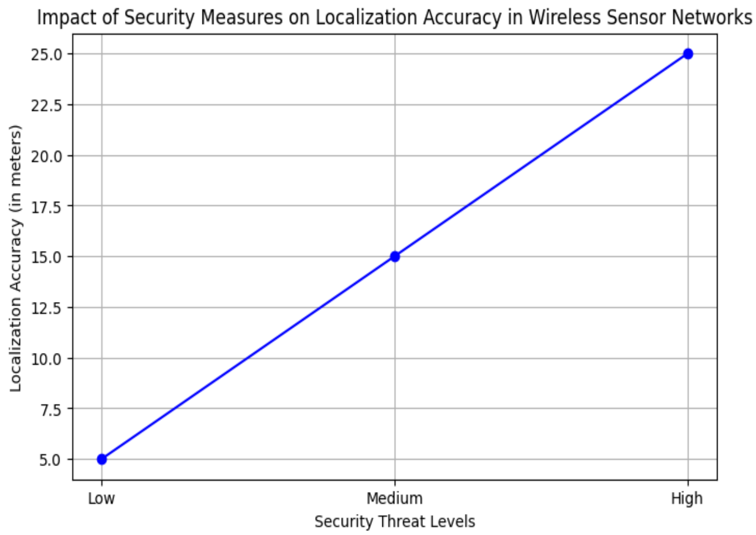

Figure 13: Effects of the level of security threats on the localization accuracy in wireless sensor networks

This is an illustrative figure 13 that explains why security measures like encryption, authentication, and intrusion detection systems are critical to ensuring the reliability of the systems. These security measures, by reducing the effects of the external threats, will ensure that the accuracy and effectiveness of the localization system remain intact in emergency or high-risk conditions, which require fast and accurate localization.

5 Conclusions

This work discusses the development, implementation, and evaluation of an innovative emergency response system and localization system to deploy in subject campuses. By incorporating heterogeneous sensor modalities such as the acoustic, thermal, and gas/smoke, vibration, and electrical fault sensors into a robust DOA estimation framework, it is possible to have an emergency event fast and accurately localized and dispatched in real-time to the relevant responders. High-resolution DOA estimation (e.g., MUSIC) with high accuracy, like event and location determination, is performed using the integrated methodology based on space signal processing techniques and software. Also, security was introduced to ensure the protection of the wireless ad-hoc sensor network to provide integrity and confidentiality of data, as well as reduce the susceptibility to attacks, including interference and unauthorized access. Among the experiments and simulations conducted, the package demonstrated high results in particular critical metrics: it achieved an excellent result in location precision, it had nearly zero latency in detection, it achieved perfect accuracy in identifying events in the event-type mode (97% and higher), and it achieved a result of more than 40% shorter time dispatch compared to manual methods. The system also had approximately 99% uptime over a 30-day duration, as well as graceful degradation in the event of node failure. The resilience of the system, precision in its spatial coverage, and security effectiveness are also demonstrated by sensitivity analysis using ROC, GDOP, and error-confidence parameters, and are helpful in optimizing the location of sensors, area covered, and the mitigation of threats. The research paper is concerned with the opportunities of sensor-fused, AI-equipped emergency localization systems in smart campuses, and the future direction of the study will be on the improvement of security measures and scalability to larger, more complex applications. Future studies may involve increased security measures to thwart sophisticated cyber-attacks and improve the strength of data, enhance system scalability to bigger systems such as urban or multi-campus systems, and use machine learning and AI to forecast and categorize emergencies and minimize errors more accurately. Also, it would be helpful to optimize sensor energy efficiency and cost to implement long-term deployment, and to design real-time adaptive response mechanisms based on dynamic risk evaluation, which may increase further system performance, scalability, and effectiveness in smart campuses and others.

References

[1] Aboumahmoud, I., Muqaibel, A., Alhassoun, M., & Alawsh, S. (2021). A review of sparse sensor arrays for two-dimensional direction-of-arrival estimation. *IEEE Access*, *9*, 92999-93017.

[2] An, D., Chang, S., Hwang, M., Youn, Y., Kim, D., Lee, C., & Hong, W. (2024). Diagnosis and modification of propagating electromagnetic waves using doa systems and em skins. *IEEE Transactions on Antennas and Propagation*, *72*(4), 3629-3640.

[3] Chen, M., Mao, X., & Wang, X. (2023). Performance analysis of deep neural networks for direction of arrival estimation of multiple sources. *IET Signal Processing*, *17*(3), e12178. https://doi.org/10.1049/sil2.12178

[4] Dibiase, M., Mohammadgholiha, M., & De Marchi, L. (2022). Optimal array design and directive sensors for guided waves doa estimation. *Sensors*, *22*(3), 780. https://doi.org/10.3390/s22030780

[5] Dupont, A. (2024). Design and Optimization of Antenna Arrays for 5g Communication Systems. *International Academic Journal of Science and Engineering, 11*(4), 37–41. https://doi.org/10.71086/IAJSE/V11I4/IAJSE1169

[6] Foutz, J., Spanias, A., & Banavar, M. (2022). *Narrowband direction of arrival estimation for antenna arrays*. Springer Nature.

[7] Gopinath, M., & Muthazhagu, M. (2025). Investigating Data Science Approaches for Predictive Maintenance in Maritime Fleet Operations. *Indian Journal of Information Sources and Services, 15*(4), 177–182. https://doi.org/10.51983/ijiss-2025.IJISS.15.4.20

[8] Hayward, S. J., van Lopik, K., Hinde, C., & West, A. A. (2022). A survey of indoor location technologies, techniques and applications in industry. *Internet of Things*, *20*, 100608. https://doi.org/10.1016/j.iot.2022.100608

[9] Huang, S. Y., & Wu, R. B. (2022). Positioning for search and rescue in GPS-denied area by distributed WiFi RSS-based DoA modules. *IEEE Access*, *10*, 76105-76113.

[10] Hussein, F. A., Yaseen, M. T., & Mustafa, M. O. (2025). The Future of Intelligent Industrial Systems: PLC, Node-RED, and IoT/IIoT. *AUIQ Technical Engineering Science*, *2*(2), 5. https://doi.org/10.70645/3078-3437.1034

[11] Jagtap, M. S. G., & Kunte, A. S. (2023). Improved Direction of Arrival Estimation using Multiple Signal Classification (MUSIC) Algorithm with Decomposition and Normalization. *International Journal on Recent and Innovation Trends in Computing and Communication, 11* (7s), 263-268.

[12] Javed, N. A., Rajkumar, Y., & Kaliyamurthie, K. P. (2025). IoT Fundamentals: Platforms, Architectures, and Sensor Technologies. *IoT for Smart Grid: Revolutionizing Electrical Engineering*, 17-41.

[13] Joy, A., Jacob, J., & Roy, B. (2025). High-Speed Hardware Edge Detection Implementation on FPGA Using Pipelined Sobel and Canny Algorithms. *Archives for Technical Sciences, 2*(33), 472–482. https://doi.org/10.70102/afts.2025.1833.472

[14] Lee, H., Kang, T., Jeong, S., & Seo, J. (2022, June). Evaluation of RF fingerprinting-aided RSS-based target localization for emergency response. In *2022 IEEE 95th Vehicular Technology Conference:(VTC2022-Spring)* (pp. 1-7). IEEE.

[15] Li, C., Liang, G., Qiu, L., Shen, T., & Zhao, L. (2023). An efficient sparse method for direction-of-arrival estimation in the presence of strong interference. *The Journal of the Acoustical Society of America*, *153*(2), 1257-1271.

[16] Liang, L., Shi, Y., Shi, Y., Bai, Z., & He, W. (2022). Two-dimensional DOA estimation method of acoustic vector sensor array based on sparse recovery. *Digital Signal Processing*, *120*, 103294. https://doi.org/10.1016/j.dsp.2021.103294

[17] Liu, M., Cao, H., & Wu, Y. (2020). Improved subspace-based method for 2D DOA estimation with L-shaped array. *Electronics Letters*, *56*(8), 402-405.

[18] Magiera, J. (2021). Detection and direction-of-arrival estimation of weak spread spectrum signals received with antenna array. *Electronics*, *10*(21), 2566. https://doi.org/10.3390/electronics10212566

[19] Mestre, X., & Vallet, P. (2020). On the resolution probability of conditional and unconditional maximum likelihood DoA estimation. *IEEE Transactions on Signal Processing*, *68*, 4656-4671.

[20] Nagaraju, L., Lokesh Dharma Theja, C., & Kumar, P.K. (2023). LFM based Wideband DOA Estimation using Deep Neural Network at Low SNR. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(9s), 607–614.

[21] Nurlan, Z., Zhukabayeva, T., Othman, M., Adamova, A., & Zhakiyev, N. (2021). Wireless sensor network as a mesh: Vision and challenges. *IEEE access*, *10*, 46-67.

[22] Oudah, A. Y., Alubady, R., & Shaker, L. M. (2025). Recent Trends in Network Technologies: A Comprehensive Review. *AUIQ Technical Engineering Science*, *2*(3), 5. https://doi.org/10.70645/3078-3437.1045

[23] Oztoprak, A., Hassanpour, R., Ozkan, A., & Oztoprak, K. (2024). Security challenges, mitigation strategies, and future trends in wireless sensor networks: A review. *ACM Computing Surveys*, *57*(4), 1-29.

[24] Pandey, A., Hasan, M., & Raj, A. B. (2022, November). Space Time Adaptive Processing for High Signal to Clutter Ratio Target's Detection Radar System. In *2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)* (pp. 1298-1302). IEEE.

[25] Pethe, R., Puranik, P., & Kasetwar, A. (2025, July). Enhancing the Performance of Wireless Sensor Networks Through AODV Protocol in Wireless Mesh Network. In *International Conference on ICT for Sustainable Development* (pp. 102-112). Cham: Springer Nature Switzerland.

[26] Shaker, L. M., Isahak, W. N. R. W., & Mahdi, A. S. (2025). Architectural Optimization of Façade Design Using Nano-Ceramic Films for Green Buildings in Baghdad's Hot Climate. *AUIQ Technical Engineering Science*, *2*(2), 10. https://doi.org/10.70645/3078-3437.1039

[27] Shari, R., & Jacob, S. (2022, November). Comparative study of DOA estimation algorithms. In *2022, IEEE 19th India Council International Conference (INDICON)* (pp. 1-4). IEEE.

[28] Shouffi, O., Shaglil, I., Stayanova, K., & Benotsmane, R. (2024, May). Design and implementation of DOA algorithms for innovative antenna systems. In *2024 25th International Carpathian Control Conference (ICCC)* (pp. 1-6). IEEE.

[29] Sun, T., Ge, Q., Wen, Y., Guo, Y., & Li, M. (2022). An Under-Sampling Array Signal Processing Method Based on Improved Hadamard Matrix. *Applied Sciences*, *12*(21), 10769. https://doi.org/10.3390/app122110769

[30] Van, C., & Shimada, T. (2025). FusedVisionNet: A Multi-Modal Transformer Model for Real-Time Autonomous Navigation. *International Academic Journal of Innovative Research, 12*(2), 32–42. https://doi.org/10.71086/IAJIR/V12I2/IAJIR1215

[31] Wang, M., Gao, F., Jin, S., & Lin, H. (2019). An overview of enhanced massive MIMO with array signal processing techniques. *IEEE Journal of Selected Topics in Signal Processing*, *13*(5), 886-901.

[32] Yadav, S. K., & George, N. V. (2021). Coarray MUSIC-group delay: High-resolution source localization using non-uniform arrays. *IEEE Transactions on Vehicular Technology*, *70*(9), 9597-9601.

[33] Yang, Y., & Jiang, G. (2023). High-accuracy DOA estimation via parallel sparse nested array with extended aperture and reduced mutual coupling. *Electronics Letters*, *59*(17), e12930. https://doi.org/10.1049/ell2.12930

[34] Zhou, H., Liu, Z., Luo, L., Wang, M., & Song, X. (2023). An improved two-stage spherical harmonic ESPRIT-type algorithm. *Symmetry*, *15*(8), 1607. https://doi.org/10.3390/sym15081607

Authors Biography

Atheer Y. Oudah aalmuttar is a researcher and academic at Al-Ayen University, Iraq, with a specialization in computer science and information technology. He earned his Ph.D. in Computer Science–Information Technology from Voronezh Government University, Russia, in 2019, following a Master's degree in Computer Science–Information Technology from Universiti Utara Malaysia in 2012, and a Bachelor's degree in Computer Science from Thi-Qar University in 2007. His research expertise covers artificial intelligence, computational modeling, signal processing, biomedical systems, and communication networks, and he has published more than 50 peer-reviewed articles in collaboration with international scholars from Iraq, China, India, and Europe. His work has accumulated over 590 citations, reflecting strong academic impact, and his recent research explores 5G technologies, blockchain applications, wireless sensor networks for renewable energy, and AI-driven intrusion detection, bridging advanced computational methods with real-world challenges in engineering, sustainability, and health informatics.

Raaid Alubady received his Ph.D. in Information Technology/Computer Networks from Universiti Utara Malaysia in 2017, following a Master's in Information Technology from UUM in 2012, a Higher Diploma in Data Security from the Iraqi Commission for Computers and Informatics in 2002, and a Bachelor's in Computer Sciences from the University of Babylon in 2001. He is an Assistant Professor of Computer Networks at the College of Information Technology, University of Babylon, Iraq, with over 20 years of academic experience. His research interests focus on future internet architectures (ICN and NDN), wireless and sensor networks (MANET, WSN, WBAN, IoT), blockchain technology, fog and cloud computing, routing protocols, security, and performance analysis. Dr. Alubady is an active IEEE member, having served three consecutive terms as an executive member of the IEEE student chapter and elected vice chair of the IEEE Student Branch at Universiti Utara Malaysia in 2016. He is also affiliated with several international and national societies, including the Internet Society Malaysia Chapter, Internet of Things SIG Chapter, Machine Intelligence Research Labs (USA), ICANN (USA), and the Iraqi Association for IT Specialists. He has published over 30 scientific papers and contributed as a reviewer and editorial board member for various international journals and conferences, including the Journal of University of Babylon. His career reflects a strong commitment to advancing research and development in networking, security, and intelligent communication systems.

Lina M. Shaker is a distinguished researcher with a noteworthy academic profile at Al-Ayen Iraqi University with a SCOPUS h-index of 27, she stands as a recognized authority in her field. Dr. Lina has received her Ph.D from Universiti Kebangsaan Malaysia. Lina has demonstrated her commitment to advancing knowledge through the successful filing of 5 patents, each contributing to the innovative landscape in her area of expertise. Her prolific research output includes the publication of +70 research articles and reviews in high-ranked journals, indicative of the quality and impact of her work in the scientific community. Lina's dedication to rigorous research and her ability to contribute valuable insights to the academic discourse are reflected in the acclaim she has received. Currently, Lina's research interests are primarily focused on the optical design and fabrication of polymeric contact lenses utilizing nanotechnology for vision correction through optical and network optimization. This innovative approach underscores her commitment to leveraging cutting-edge technologies to enhance visual correction methods and improve overall eye health. In addition to her work on contact lenses, Lina is actively involved in the synthesis of corrosion inhibitors. Her research in this domain showcases a multifaceted approach, addressing challenges in materials science and engineering. Lina M. Shaker's expertise, as evidenced by her patents, publications, and research focus, positions her as a dynamic and influential figure in the realms of nanotechnology, vision correction, and corrosion science, optical network. Her commitment to pushing the boundaries of knowledge underscores her dedication to making meaningful contributions to the scientific community and beyond.

Dr. Ahmed A. Al-Amiery is a recognized researcher and professor in the field of applied chemistry. According to publicly available information, he has held a full professorship at University of Technology - Iraq (Baghdad), where he served as head of the Energy and Renewable Energies Technology Center. Completed B.Sc. in General Chemistry (1998), Al-Mustansiriya University, Iraq. M.Sc. in Organic Chemistry (2001), University of Baghdad, Iraq. Ph.D. in Organic Chemistry (2007), Al-Mustansiriya University, Iraq. Dr. Al-Amiery's work centers on the synthesis of novel organic molecules with practical applications — notably as corrosion inhibitors, antioxidants, antimicrobial agents, and in other applied-chemistry contexts. He has authored hundreds of scientific publications and holds multiple patents in these fields. His research portfolio includes investigations into eco-friendly corrosion inhibitors, organic molecule design, and materials chemistry, often combining experimental and theoretical approaches. Dr. Al-Amiery is listed among the researchers with high impact, recognized by international bodies and indexing services for his prolific output. He has contributed as editor and reviewer in various international journals, strengthening his global scientific outreach.