Bulletin of Electrical Engineering and Informatics
Vol. 13, No. 2, April 2024, pp. 947~954
ISSN: 2302-9285, DOI: 10.11591/eei.v13i2.5833

A comprehensive survey on several fire management approaches in wireless sensor networks

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Article Info

Article history:

Received Jan 22, 2023
Revised Aug 24, 2023
Accepted Sep 20, 2023

Keywords:

Clustering
Data aggregation
Fire management
Malicious cognitive radio
Security
Wireless sensor networks

ABSTRACT

The majority of the fires are activated through environmental reasons although a minority of them are self-activated. To detect fires several safety systems were introduced. There are wired systems, cameras, satellite systems, and bluetooth feasible to provide a complete image of the world but after a long search period. These systems are not perfect since it prevents fire from finding just at the time, the fire initiates. But, recent technological development in wireless sensor networks (WSN) has spread out its fire detection application. A comprehensive survey on several fire management approaches in WSN propose to discuss various fire detection approaches like early fire detection, energy efficient fire detection, mobile agent-based fire detection, unmanned aerial vehicle (UAV)-based fire detection, threshold-based fire detection, machine learning based fire detection and secure fire detection approaches. Moreover, the comprehensive tabular study of the fire management technique is given that will assist in the suitable selection of approaches to be applied for the detection of fire. Furthermore, WSN uses the clustering method to minimize redundant dataandsecure fire detection approaches collect authenticated data related to fire detection. Early fire detection approaches detects the fire early. Machine learning algorithm detects the fire efficiently.

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1. INTRODUCTION

When a wildfire burns out of control, the cost to society and the living conditions can be beyond measure. Regrettably, identifying fire is typically feasible only when it has earlier increased over a massive area, making fire control an important challenge. Thus, an early-stage recognition of fire is essential [1]. Hardware-based detection methods provide lesser accuracy with the great event of false alarms; as a result, it misclassifies actual fires. It is not appropriate for discovering fires breaking out in large regions, for example, buildings, warehouses, fields, forests, and oil reservoirs [2]. Several approaches for detecting the fire comprise noticing from watch towers and utilize of satellite images [3]. Regrettably, these are not proficient because of various reasons. Wireless sensor networks (WSNs) characteristically comprise thousands of sensor nodes to observe their surroundings, gather data, and move to further processing. Generally, WSNs is a resource-constrained; therefore, energy efficiency is critical for WSNs applications. Clustering is a familiar method in WSN, grouping nodes to handle various tasks in a disseminated way. Though clustering approaches are recognized to improve energy expenditure, several quality-driven targets can be appreciated through clustering. Yet, the WSNs the sensor nodes require to be established heavily to compensate for collecting standard data. But, repeated observing and the data forwarding created unnecessary samples that can additionally utilize sensor node energy and bandwidth resources. Table 1 illustrates the comparison of the satellite system, cameras, and WSN.

Table 1. Illustrates the comparison of the satellite system, cameras, and WSN

Satellite [3]	Cameras [2]	WSN [4]
It notices for forest fires endure harsh limitations resulting in a failure in quick and efficient control for forest regions	It requires to improve to minimize the false alarms because of several dynamic processes	It is an efficient method for forest fire detection
An optical and infrared spectral emission produced through a small fire, in the early stage of a forest prior to its dissemination over a broad area, possibly too weak to identify via satellite	The complexity of processing landscape images due to their changing nature and the dynamic events	They can offer all the required details that influence the surroundings at all moments precisely
A satellite is generally designed to execute several diverse functions and a satellite system is not cost-effective. The satellite function cannot time span to immediately offer details about the forest fire inside the forest area	This system is designed to cover large regions with lesser camera towers	They can cover all areas, in addition to their scalable network

Furthermore, it minimized the lifetime. Hence, data redundancy minimization is a vital issue. Additionally, in cluster-based WSN, cluster heads (CHs) use more energy because of aggregating the data from cluster member nodes and forwarding the aggregated data to the base station (BS) [5]. Hence, sensor nodes should utilize data aggregation for data forwarding that reduced the duplicated data [4]. Table 2 demonstrates the metrics comparison for fire detection.

Table 2. Metrics comparison for fire detection

Metrics	Satellite system [3]	Cameras [2]	SN [4]
Detection delay	Very high	High	Low
Information on fire behavior	Yes	-	Es
Accuracy of fire detection	Average	Average	High
Efficiency	Lesser	Average	Greater
Fault alarm	Lesser	Average	Lesser

Due to the high requirements and usages of WSN, it is susceptible to attacks because of that its security has to seclude correct. Since sensor nodes are distributed arbitrarily, no surveillance is there due to which an attacker and counter adversary can corrupt or damage the network or remove information from it. If an adversary attacks the sensor node can lead to data break or malfunctioning. The applications regarding WSNs call for a vast deal of security because they work separately and in unfriendly environments. To evade these circumstances, the sensor nodes should be durable against attackers. Hence, sensor node authentication and data security is an important challenges of fire detection in the WSN.

2. VARIOUS FIRE MANAGEMENT TECHNIQUES

This section describes various fire management techniques introduced by several researchers by using WSN with incorporate mobile communication to detect fire. Artificial intelligence (AI) and machine learning techniques perform various sets of functions determined by the harshness of the fire hazard, but each approach has advantages and restrictions. These techniques are described below.

2.1. Unmanned aerial vehicle-based fire detection approaches

Unmanned aerial vehicles (UAVs) are increasingly used in fire observation and detection to their great mobility and capability to cover regions at different altitudes and positions [6]. Traditional fire detection methods are typically established on the red, green, and blue (RGB) color model, but their speed and accuracy necessitate further improvements. Hybridization-based meta-heuristic algorithm using a UAV for monitoring the forest fire efficiently and minimizing the energy utilization. Initially, differential evolution and the self-organized multi-agent are used to generate data gathering in a combined path that evades a blind search in a complex solution space. Next, a local search algorithm is used to enhance the transmission. However, this approach does not verify data collection [7]. The kalman filter-based method is introduced to measure wildfire growth that is gathered through UAVs. It is used to measure the wildfire dissemination behavior and firefront form. It facilitates by increasing a scalar field wildfire method and applying the Kalman filter to measure the model parameters [8]. Bio-inspired localization in UAV for wildfire detection and observing. A hybrid gray wolf optimization algorithm to achieve high localization accuracy. This approach enhances efficiency. It is an efficient routing tree; thus, it minimizes the routing delay and the transmissions [9]. UAVs with incorporated AI technology are used for uninterrupted fire detection services [10]. However, UAV-based fire detection approaches make an additional cost. Besides, investigators are applying deep learning (DL) algorithms to sense the fire utilizing UAVs [11]–[13]. Though, it cannot be appropriate for large region fire identification [14]–[18].

2.2. Early fire detection approaches

This section explains a WSN for early recognition of fires. WSN contains sensor nodes to gather data from the environment, and these sensor nodes forward the information to a BS [19]. A fire detection process to observe several types of indoor building fires. This proposed fire detection method integrates both noticing and recognition stages to efficiently operate diverse sensor signals and notice fire epidemic at a preliminary phase. The introduced fire observing process collects data from the environment via multiple sensors perceptive to evaluate several elements discharged from fires. Next, the gathered data is applied through a resemblance matching-based fire identification method that catch various design and noticed the epidemic of fires with small false alarms [20]. It uses temperature and humidity sensors for detecting fire [21]. A neural network method is used for detecting the fire. This framework contains two phases a segmentation module to take out the forest fire shape, and a categorization phase recognizes whether the detected fire region is real or not. This approach reached moderately competitive segmentation accuracy and consistent detection. Though, this approach presents several limitations such as color and spread difference it is difficult to measure the fire [22]. An internet of thing (IoT) based fire alarm system provides a message alert to the owner and fire station in case of an emergency. This research differentiates states of the surroundings in terms of sleep, passive or active state using a decision tree algorithm. Hence a low-cost, IoT system is developed which is ideal as a fire safety solution in residential areas and hospitals. But, this approach cannot able to detect harmful gases. This approach does not present a self-testing module; as a result, device failure can occur [23]. Also, fog and snows location fire cannot detects efficiently [24]. However, this approach does not forward precise information. In addition, these approaches can’t detect the fire efficiently due to malicious sensor nodes, or inaccurate fire detection in the network.

2.3. Mobile agent based fire detection approaches

In WSN, the mobile agent helps to detect the fire and this agent increases the lifetime [25]. AI technology is applied to build an intelligent dynamic migration route-solving method. The fire active evacuation route computation while a fire emerges and enhanced ant colony optimization (ACO) assists in efficiently diverting the fire point. The ACO forms the optimal route by temperature, smoke awareness, and carbon monoxide awareness. However, this approach increases energy utilization in the network [26]. Cluster-chain mobile agent routing that forms the WSN and sensor nodes are formed the clusters operate in two modules. In the first module, the sensor nodes in every cluster build a chain to execute the data aggregation inside the clusters. In the second module, a mobile agent is sent out from the destination node to gather the aggregated data from every cluster or CH node. This approach improved the network lifetime and minimized energy utilization. Though, this approach is idle of the network security [27]. These approaches use the additional device; thus, it builds an additional expenditure.

2.4. Threshold method-based fire detection approaches

Threshold approaches incorporated a back-propagation neural network (BPNN) for removing smoke advanced very high-resolution radiometer. The BPNN approach determines emission estimations among smoke, cloud, and land, it can able to recognize the region enclosed by smoke [28]. An enhanced algorithm was established on their earlier model applying BPNN. The BPNN approach utilizes the multi-threshold procedure to recognize the smoke [29]. However, the traditional threshold approach is simply affected by thick smoke, cloud that cause omission errors and false positives [30]. Next, the DL algorithm offers a fine spatial solution, although the temporal solution is comparatively small. High temporal is serious to observe the fire. Furthermore, exact and timely fire observing is a demanding job because the threshold method simply failed to the false alarm causing little clearings, and omission error via thick smoke.

2.5. Machine learning algorithm-based fire detection approaches

Fire is a significant ecosystem procedure and it acts as a complex task in a world ecosystem. Sometimes, wildfires are extremely creating natural disasters. To minimize this disaster, wildfire identification is an important concept. Identification of fire is particularly hard utilizing traditional ways of smoke sensors installed in the buildings. They are slow because of their earliest technology. The machine learning approaches detect fire efficiently [31]. But, convolution neural network (CNN) algorithm significantly examines the assessment of AI for observation and forwarding alerts. It focuses on cost-efficient and it detects fire accurately [32]. Fire CNN utilizes a multi-scale CNN approach that efficiently detects the precise features of fire spots [33]. Traditional machine learning utilizing feature extraction gives better fire detection and a lesser miss detection ratio, even if it needs vast field information. It involves hand-crafting characteristics incrementally applying domain information, time-expenditure, dull, and error-prone procedures [34]. DL algorithm is a better learning capability, well adaptability, and better scalability. Thus, many investigators utilize the DL method for detecting fire [35]. It can determine the difficult patterns in huge information by utilizing layers. The deep neural networks (DNN) approach also uses to notice wildfires. A weight selection strategy is capable to detect wildfires precisely related to the usual DNN [36]. A CNN model, SmokeNet incorporates the aid of channel direction and space to improve the attribute demonstration of view categorization. It provides great reliability among forecasts and real categorization outcomes [37]. DL-based fire classification approach using a CNN method by transfer learning to categorize the fire and non-fire [38]. CNN-based super-resolution algorithm is developed to detect active fire [39], [40]. DL approach applies a CNN method and long short-term memory (LSTMs) can efficiently differentiate burnt areas with superior accurateness than earlier approaches [41]. Adopted the DL method to categorize the fire smoke. But, it cannot detect the fire position [42]. Over the past decades, DL methods promoting major advances in AI, for example, generative adversarial networks, deep CNN, recurrent neural networks, and LSTM. But it is hard to notice the fires at a pixel level, because of the lesser spatial resolution and the subtle target of the fire.

2.6. Clustering with energy efficient routing based fire detection approaches

Energy-efficient systems suggest two functions that cooperate with energy-efficient data processing and transmission to improve network lifetime. However, this approach does not provide security of WSN [43]. An adaptive duty-cycled hybrid approach is used to predict the fire with the energy-efficiency. In addition, duty-cycle scheduling is applied to proficiently compute the environmental risk of a fire happening. The relationship between fires and temperature is approximately irrelevant, while humidity, wind speed, and rainfall connection are all important. Hence, fire possibility raises when the speed of the wind is high, low humidity, and little [44]. Heterogeneous multimedia WSN to reduce the communication of visual data. A lightweight DL method is introduced to enhance the accuracy of detection and minimize the traffic between the edge devices and the destination. It improves energy efficiency and detection accuracy. But, this approach can't improve node authentication or data security [45]. A localization technique using the support vector machine algorithm for predicting the fire. The semi-supervised classification method is introduced to deal with this issue by separating the region into various sectors like high, medium, and low active. This approach can capable to forecast the state of the fire zone with the highest accuracy. It improves the network lifespan and minimizes congestion [46]. Table 3 demonstrates the comparison among energy-efficient routing protocols.

the highest amount of energy because of cluster overlapping, choosing lower energy nodes as a CH, hotspot issue, and faraway communication distance. The harmony search algorithm is applied to reduce the intra-cluster distances between the CH and their cluster members and it enhances the energy allocation. This approach measures the temperature for detecting the fire. This approach uses a fuzzy c-means clustering algorithm to improve the lifetime [47]. The integrated modified genetic algorithm (ModifyGA) based chooses the CH to enhance the lifetime. The ModifyGA method is raised by integrating dynamic sensing range and criteria used for the rising fitness function. The ModifyGA fulfills several constraints for optimizing intra-cluster distance, efficient utilization of node's energy, minimizing hop count, and supporting the selection of extremely capable CH nodes [48]. Node clustering and data aggregation methods are possible to maintain the huge number of devices and meet several service quality necessities. Non-orthogonal several access-enabled two-stage communication architectures to facilitate huge IoT communications [49]. The cluster method's objective is to extend the lifespan [50]. Yet, the CH performs operations like data gathering, data aggregation, and data forwarding that make the CH dead easily. This section, compares different clustering protocols in WSNs like low-energy adaptive clustering hierarchy (LEACH), threshold sensitive energy efficient sensor network (TEEN) harmony search algorithm (HSA), particle swarm optimization (PSO)-HAS, PSO semi-distributed (PSO-SD) two-tier PSO protocol for clustering and routing, integrated clustering for cuckoo search and harmony search (iCSHS). The evaluation is carried out concerning the overall objective, clustering type, clustering stability, energy efficiency, scalability, and complexity.

In WSN, energy conservation is a major dispute in sensor applications because of the inadequate sensor resources which are not forever feasible to be substituted. The energy-efficient routing protocol can improve the network lifetime. In WSN, to accumulate energy, a data aggregation method is applied to reject the data redundancy also energy-efficient routing is broadly utilized to decide the optimal route from the sender to the receiver. Q-learning-based data-aggregation-aware energy-efficient routing utilizes reinforcement learning to enhance the rewards regarding transmission energy, efficiency, and node energy to receive an optimal route [51]. An aggregation-scheduling method is used for improving energy-efficient in WSN. This approach contains two modules such as aggregation and scheduling. In the aggregation module, every node's objective is to minimize the highest amount of data forward occasionally to the CH established on the multi-aggregation method. In the next module, the sleep/active model has applied all sensor nodes and concerns a scheduling method to switch all sensor nodes creating similar data; the CH initially converts the interrelated nodes into a graph before pertaining to a coloring-map algorithm and a scheduling method for electing active nodes. This approach saves energy and improves the lifetime [52]. Ensemble clustering and markov chain mechanism can efficiently minimize redundant information. The davies-bould in index is adjusted to choose an optimal cluster [53]. All data aggregation approaches are minimized both the delay and overhead. It improved the network scalability and increases energy conservation. Though, the malicious or adversary sensor nodes present inside the network create an additional delay and packet losses.

Table 3. Comparison among energy-efficient routing protocol

Protocol	Clustering type	Objective	Clustering stability	Energy efficiency	Scalability	Complexity
TEEN [43]	Possibility centralized	Changing CH based on threshold	Short	Average	Great	High
HSA-N	Centralized	Minimum distance with energy	Great	Average	Fine	High
PSO-HSA [45]	Centralized	Minimum distance with energy	Short	Great	Great	High
PSO-SD	Centralized	Minimum distance, node hop count energy	Great	Moderate	Fine	Average
TPSO-CR	Centralized	Link quality with coverage and energy	Short	Moderate	Fine	High
LEACH [50]	Random	Changing CH based on random	Short	Small	Restricted	Low
iCSHS [51]	Distributed	Node degree, intra distance, energy with coverage		Moderate	Average	High

2.7. Secure routing-based fire detection approaches

In cluster-based WSN balances energy efficiency and enhances the lifetime. Though, it is susceptible to several attacks. Compromised CHs may turn malicious and initiate attacks in that they lose part of the packets. A clustering algorithm is used for identifying a selective forwarding attack. This approach separates malicious CHs based on cumulative forwarding rates [54]. This approach uses a fuzzy logic method to compute the probability of fire and identify the faulty nodes. It contains two types of faults such as hard fault and soft fault. The hard fault indicates the sensor nodes are unable to communicate with neighbor nodes due to any hardware device damage or battery consumption. A soft fault is when the sensor nodes transmit the data from one to other but, forward incorrect data. Thus, it is a vital and demanding task to discover these types of faulty nodes [55]. An optimized fuzzy logic-based fire observing that decides in avoiding mine fire. But, each sensor interpretation is very demanding. Thus, the binary particle swarm optimization method improves the fuzzy system, which removes unnecessary but conserves the accuracy of event detection [56]. A vision-based fire detection method for observing private spaces while preserving the privacy of the occupant. This approach uses an infrared camera to capture images so that the privacy of occupants is protected. However, these approaches increase energy expenditure [57]. Table 4 (in Appendix) illustrates the comparison of various fire management techniques in WSN.

3. CONCLUSION

This paper presents various fire management techniques in WSN. This paper briefly analyzed some fire detection approaches like early fire detection, clustering with energy efficient fire detection, mobile agent-based fire detection, UAV-based fire detection, threshold-based fire detection, machine learning-based fire detection, secure fire detection approaches description, advantages, and disadvantages. In this study, several researchers by applying early fire detection, energy-efficient routing, secure fire detection, and machine learning algorithms separately; as a result, a better result is not achieved. In addition, today's world requirement for fire detection is not satisfied. Hence, in the future, we propose secure fire detection and energy-efficient clustering in the WSN. Here, the temperature and humidity sensor nodes observe the surrounding information efficiently. Then, an early fire detection algorithm is to predict and makes a decision related to fire and forward this authenticated information to the BS via cluster routing. Furthermore, we will use a cryptography algorithm to transmit secure data in the WSN.

APPENDIX

Table 4. Comparisonofvarious fire management techniques in WSN

Fire detection methods	Remarks	Advantage	Disadvantage
UAV-based fire detection [6]-[9]	UAV detects the fire it integrated an AI system	Minimize energy consumption since it is rechargeable. Minimize the delay due to, it reaching the destination earlier	It can't able to use large-scale networks because it works on short distances. It increases the additional cost. It does not verify data collection
Early fire detection [19]-[22]	Fire detection based on alarm it integrates both noticing and recognition stages	Detect the fire earlier because it predicts the fire based on parameters. Low cost	Color and spread difference is difficult to measure the fire inaccurate fire detection lacking node authentication due to it concentrates only on early fire prediction. Device failure occur fog and snows location fire cannot detect efficiently
Mobile agent based fire detection [25]-[27]	The mobile agent helps to detect the fire it uses an AI system	Improve the lifetime enhance the energy efficiency	Idle of the network security. It uses additional devices; thus, it builds an additional expenditure
Threshold-based fire detection [28]-[30]	Detect the fire based on the threshold	It provides fine spatial resolution. Multi-threshold to identify smoke efficiently	In addition, precise and suitable observing of fire is a demanding role because the threshold-based approaches simply accept false alarms false alarm causes little clearings and omission error via thick smoke
Machine learning-based fire detection [31]-[35]	Detect the fire based on learning algorithms	It improves fire detection efficiently it provides accurate fire detection. Low false positive rate	However, it is complicated to notice the fires at the pixel stage, because of lesser spatial resolution and the subtle target of the fire
Clustering with energy efficient method-based fire detection [43]-[45]	The clustering method balances energy and enhances the lifetime the data aggregation method eliminates the redundant data	The clustering method increases energy efficiency since it uses a sleep/active model increase data accuracy the clustering concept improves scalability the data aggregation method minimizes the routing overhead	Lacking node authentication or data security since CH compromised easily. The malicious or adversary sensor nodes present inside the network create additional delay and packet losses in the network. Increase delay since CH dead easily
Secure fire detection [54]-[57]	Detect the fire information is authenticated	Detect the malicious or attacker efficiently based on a different secure algorithm	Increase the energy expenditure

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