Indonesian Journal of Electrical Engineering and Computer Science
Vol. 31, No. 1, July 2023, pp. 281~289
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v31.i1.pp281-289

Visualization-based monitoring in early warning systems with wireless sensor networks

Minh T. Nguyen[1], Cuong V. Nguyen[2], Huyen N. Nguyen[3]
[1]Faculty of International Training, Thai Nguyen University of Technology, Thai Nguyen, Vietnam
[2]Faculty of Electronic Engineering, Thai Nguyen University of Information and Communication Technology, Thai Nguyen, Vietnam
[3]Whitacre Jr. College of Engineering, Texas Tech University, Lubbock, USA

Article Info

Article history:

Received Nov 10, 2022
Revised Feb 21, 2023
Accepted Feb 28, 2023

Keywords:

Data visualization
Early warning system
K-Means algorithm
Natural disaster
Wireless sensor networks

ABSTRACT

With the impact of global climate change, natural disasters such as prolonged drought, earthquakes, and tsunamis, have constantly increased over recent decades, putting those living in these areas in great danger. A natural disaster warning system has been established as an indispensable need to minimize possible high risks that cause human casualties. Several current natural disaster warning systems focus on building wireless sensor networks for forecasting and monitoring disasters as well as natural phenomena. This paper aims to develop a comprehensive model that integrates data visualization operations to identify and simultaneously predict threat proceedings in natural disasters. This technique can handle big data based on sensing data from wireless sensor networks and shows overview graphs about disasters' variability, floods, and earthquakes, in the areas. Based on the results collected from data visualization techniques, the system can issue alerts about the interest of the region in real time. In addition, we propose some levels for the warning system in which the networks only focus on the area with essential data that must be warned. This can save energy consumption for other areas of safety. This work shows promising points of effectiveness.

Corresponding Author:

Minh T. Nguyen
Faculty of International Training, Thai Nguyen University of Technology
Thai Nguyen, Viet Nam
Email: nguyentuanminh@tnut.edu.vn

1. INTRODUCTION

Wireless sensor networks (WSNs) support many applications in different fields, including either in civilian or military areas [1], [2]. The networks usually consist of a huge number of sensor nodes deploying in working areas. The sensor nodes collect data to be sent to a base station (BS) or data processing center for different purposes, including detection, monitoring, building scalar field maps, and early warning events [3]-[5]. There are many data collection methods in WSNs. Each routing method has specific advantages and is suitable for applications in some special tasks. All sensors are considered equal in random walks [6], [7]. Each node forwards its data to one of its neighbors based on probability. This method may increase latency for data transmission in such networks. In tree-based routing [8], [9], sensor nodes transmit their data to parent nodes and finally to be sent to the root as the BS. The routing paths are usually fixed but could be affected by some disconnections while transmitting in a vast area with many nodes. The clustering methods are quite common and stable since either the cluster heads or the routing paths of the inter-cluster can be changed [10], [11]. Hence, clustering methods are usually deployed to support WSNs detecting critical or essential events.

Natural disasters can be considered sudden effects that negatively impact the balanced ecosystem between the natural and social systems [12]. The frequent occurrence of extreme weather events in recent years has caused a lot of severe losses in many aspects of life [13]. According to a statistic of our world in data, there is an average of 60,000 dead people per year as a result of natural disasters, accounting for 0.1% of global deaths over the past decade [14]. However, it is fortunate that this abruptness is predictable based on the support of the early warning systems.

The platform of the warning systems are built based on meeting the following three primary standards: i) scientificity of the system, ii) reliability of data, and iii) accuracy of early warning. With respect to the reliability of data, sensors play an important role in aiming to provide accurate early warnings based on the ability to capture more detailed and reliable big data of the ambient natural environment [15]-[18]. Scientificity is a combination that starts from the correlation between high-risk factors and simultaneously coordinates and cooperates with other subsystems, using scientific methods and accurate data statistics. Meanwhile, accuracy and real-time capability can be achieved by analyzing and processing data of artificial intelligence, deep learning, etc. technologies [19], [20]. A specific example is the artificial neural network considered for analysis of flood management system in [21] and practically implemented in forecasting the Blue Nile river flows in Sudan [22]. The overview chart for earthquake situational analytics uses data visualization to present the condition across the area around the earthquake zone [23].

Data visualization systems provide a visual representation of the dataset, allowing users to analyze data and discover new knowledge via exploratory analysis. Based on dataset types, attributes, and domain tasks, visualization designers come up with a specific design in terms of color coding, layout, and other visual channels such as angle, shape, and size [24], [25]. The purpose is to turn data sources into visual, easy-to-observe, and understand information to clearly convey the data's full insights to the viewer. Therefore, this technique can provide an intuitive tool for finding the correlation between the cycles of natural disasters, through which people can make accurate judgments for warning disasters.

This study proposes a new direction for deploying the data visualization technique applied to predict natural disasters. The WSN is modeled with numerous sensor nodes deploying in a sensing area. A clustering algorithm partitions the network into clusters. A greedy tree algorithm is proposed to collect data from the clusters and finally to be sent to the BS. Sensing data is gathered in the database for analyzing and processing. After processing data, a visualization technique is applied to present a visual inspection for changes in sensor areas. Unusual changes are the early signs of disaster in region of interests (ROIs). This early warning sign supports humans' focus on better disaster prevention at living in those areas and minimizing loss of life and property.The analysis of the early warning system (EWS) is organized as: The next section introduces the system model of the proposed warning system. On the basis of this, section 3 describes the preliminary results of the research findings, while section 4 makes recommendations and challenges for future work. Finally, conclusions and future directions in this study are provided in section 5.

2. SYSTEM MODEL

2.1. The wireless sensor network (WSN) model

The WSN is supposed to contain N sensor nodes distributed randomly in a sensing region. The network's goal is to gather data from all nodes and send it to a data processing center or a BS. Regarding energy conservation, the network is separated into clusters, with one cluster head (CH) assigned to each cluster based on a clustering algorithm. A tree-based routing technique is developed to connect all of the CHs with the root at the BS. Based on the routing tree that connects all the CHs, all CHs collect data from their local clusters and then pass their sensor readings through the CHs closer to the BS. The BS can achieve all the data from the network based on the inter-cluster tree. Both the clustering algorithm and the tree-based routing algorithm aim to collect sending data to be sent to the BS. The Algorithm 1 divide the network into clusters. The Algorithm 2 provides a routing tree to take all sensing data from clusters to the BS. The steps in details are provided as follows.

2.1.1. Clustering Algorithm

In Algorithm 1, a certain number of sensors are chosen as CHs. The non-CH sensors send their data to the CHs they belong to. The CHs collect data among their clusters. They send the received data including their own to the BS via the inter-cluster routing tree as follows.

Algorithm 1. Clustering algorithm

1- All sensors are nominated to be CHs based on a probability as $p = \frac{M}{N}$;
2- M sensors are chosen as cluster-heads;
3- The remainder sensors choose their closest CHs to join the create M clusters.

2.1.2. Greedy tree algorithm

In Algorithm 2, the routing tree is created. All the CHs choose the ones closet to the BS to connect. Then, they can start forwarding their data to the ones closer to the BS, as shown in Figure 1.

Algorithm 2. Greedy Multiple-hop Tree formation (GMT)

```
While (the routing paths is changing)
N_H(BS) = 0; i ∈ N_c CHs
Nei = set of CH_i's neighbors
if distance [i, j] < R, where j ∈ Nei
CH(i) chooses CH(j) when N_H(j) = min{N_H(Nei)}
Name N_H (i) = N_H (j) + 1;
end if
end while (Until no change of routing paths between CHs)
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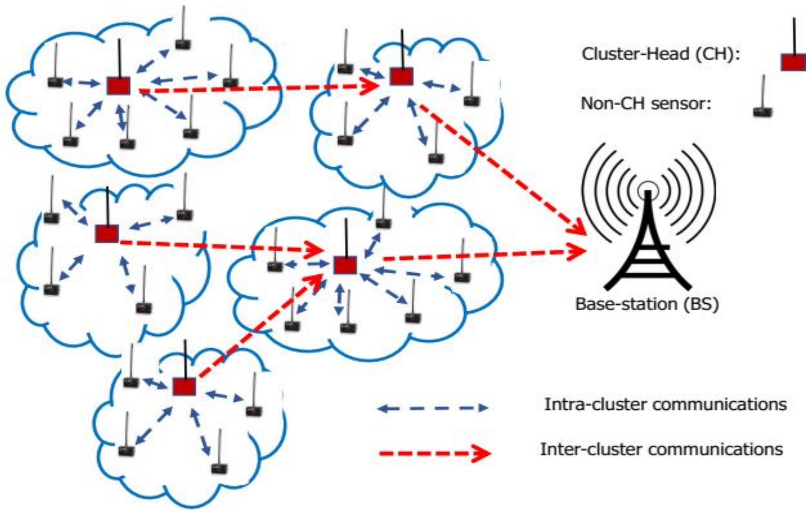


Figure 1. Illustration of the system WSN model including intra-cluster and inter-cluster communications

2.2. The early warning system (EWS) model

As described previously, the model of the EWS has mainly four processes, including data collection, data processing, predicting, and decision-making, presented in Figure 2. The structure of the EWS consists of four subsystems, as shown in:

- WSNs subsystem: A set of sensor nodes are randomly deployed in sensing areas such as high-rise buildings, mountainous areas, hydroelectric dams, or areas at high risk of tsunamis and earthquakes. They collect data on humidity, precipitation, air quality, and geological movements. With the potential for providing reliable data transmission, the data transmission database through wireless communication technologies [26].
- Database: Big data is used to manage and analyze data with multi-platform, multi-scale, and multi-discipline data [27]. Sensors might generate heterogeneous data and even comprise noise and misinformation. Therefore, the system needs to integrate multiple sources and process data, aiming to enhance the quality and completeness of data.
- Data visualization: Data visualization provides the visual representation of the data and information by different visual encodings, such as graphical elements and visual channels. The human brain's tendency to receive visual information is much easier than in other forms. The incorporation between data visualization and machine learning, discussed in [28], can learn and predict potential nature threats and formulate strategies to mitigate losses.
- Region of interests (RoIs): With the output results of the data visualization, the sensing data at the alert level is shown to the viewer. They can then drill down to see where the problems are occurring and start formulating a plan to solve them. Following this way, data visualization completely allows users to spot problems immediately and make logical decisions for predicting the RoIs.

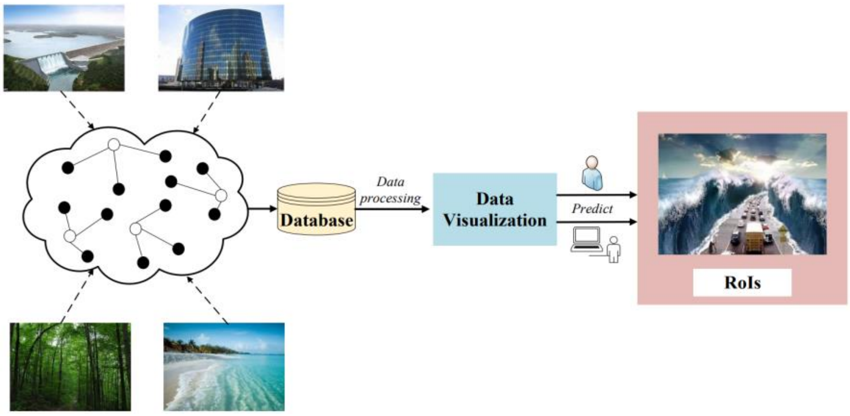


Figure 2. The system model of the early warning system using WSNs and data visualization

3. ANALYSIS AND SIMULATION RESULT

We propose a visualization-based framework, as shown in Algorithm 3, supporting monitoring in early warning systems, where the data collected by wireless sensor networks are either univariate or multivariate. Although the data characteristics may vary due to spatial processes and cross-correlation within the observed data, the difference in prediction results between the two groups is insignificant in terms of effectively monitoring multiple spatial random fields. Utilizing K-means clustering can support capturing highly unusual events characterized by experimental measurements. Furthermore, visualization supports an interactive, intuitive visual representation for monitoring and analysis in a timely manner.

We assume N sensors are deployed randomly in a sensing area. The sensing data received from all sensor nodes are sent to the central database. In the univariate case, sensors send data on the environment temperature (T) to the database, while in the multivariate case, the data may contain both temperature and humidity readings. The aim is to distinguish between danger levels so those living near a dangerous area can prepare for evacuation and promptly seek sanctuary.

Algorithm 3. Framework for data analysis

Phase 1. Data collection: the original data collected from spatial fields are gathered at a central database. The maximum feasible dimension of data is defined at this stage along with sensor selection.

Phase 2. Data preprocessing and data wrangling: As raw data often contains noise and redundancy, this stage focus on cleaning data and extract meaningful feature. Data wrangling helps transform complex data into useful, desired format for easy access, visualization and analysis.

Phase 3. Data clustering: This stage focuses on detecting natural object partitioning among data. For example, on univariate dataset which the observation is on environment temperature:

If $0 < T < 35^0C$ → Cluster 1 → Green (*Normal*)
$35^0C \leq T < 45^0C$ → Cluster 2 → Yellow (*Moderate risk*)
$45^0C \leq T < 55^0C$ → Cluster 3 → Orange (*High risk*)
$55^0C \leq T$ → Cluster 4 → Red (*Very high risk*)

Phase 4. Data visualization: Using visual encodings, data is visualized for an intuitive, straightforward representation. For example, one facet of original data is presented in Figure 3(a), the simulation results is visualized in Figure 3(b).

Phase 5. Domain knowledge incorporated for analysis: Users can filter and explore warning data clusters Figure 4(a). With interaction, domain knowledge is applied for further analysis, with in-depth view into the clusters which are especially dangerous Figure 4(b).

Suppose we are given a data set $X = x_1 \ldots\ldots x_N, x_k \in R_d$. The M-clustering problem aims at partitioning this data set into M disjoint subsets (clusters) $C_1 \ldots C_M$, such that a clustering criterion is optimized. The most widely used clustering criterion is the sum of the squared Euclidean distances between each data point x_i and the centroid m_k (cluster center) of the subset C_k which contains x_i. This criterion is called clustering error and depends on the cluster centers $m_1 \ldots m_M$ [29]:

$$E(m_1, \ldots, m_M) = \sum_{i=1}^{N} \sum_{k=1}^{M} I(x_i \in C_k) ||x_i - m_k||^2 , \quad (1)$$

where $I(X) = 1$ is true and 0 otherwise.

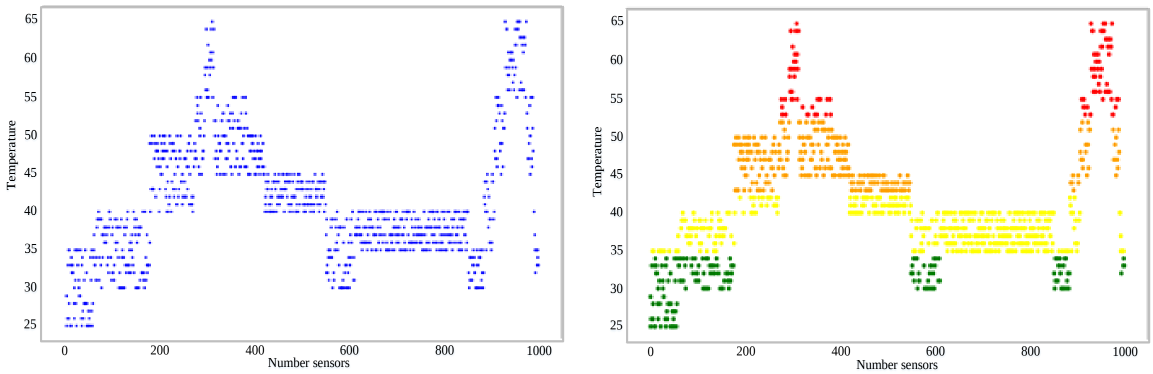
3.1. Most common measure is sum of squared error (SSE)

For each point, the error is the distance to the nearest cluster, to get SSE, we square these errors and sum them.

$$SSE = \sum_{i=1}^{K} \sum_{x \in C_i} dits^2(m_i x)\ , \qquad (2)$$

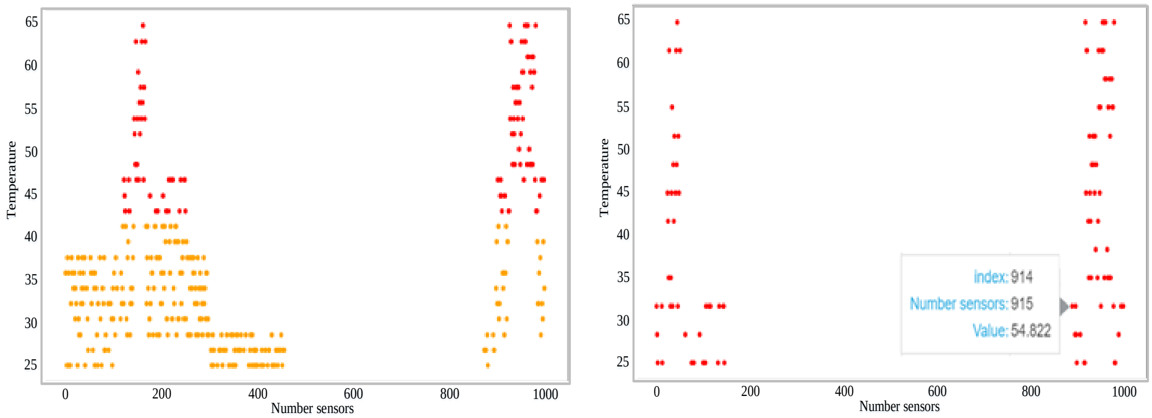
where x_i is a data point in cluster c_i and m_i is the representative point for cluster c_i.

Figure 3 visualizes sensor network data using clustering and non-clustering algorithms. Figure 3(a) shows the data of the WSN without using the data clustering algorithm. It is difficult to determine where the critical data area is or the normal data area. Figure 3(b) is a graph representing the data that has been processed through the data clustering algorithm. However, we only have an overview of the data and can make initial predictions about the data. We need to visualize the data in more detail for each location and only care about the alert data area. To do this, we use data filters, as shown in Figure 4. Figure 4(a) is the data through one filter; we have two data areas, the orange warning data area and the red special severe warning data area. To prioritize particularly severe warning zones and minimize observation time and data analysis, we use a second filter to observe only the red zone data, as shown in Figure 4(b). Thus, the data filtering process has clarified the data visualization, reducing the time of observation and data analysis a lot. We can locate the critical warning zone in the fastest time. Therefore, we can provide timely handling methods to minimize damage.



(a) (b)

Figure 3. Visualizing simulation data (a) Original univariate data and (b) with K-Means algorithm



(a) (b)

Figure 4. Interaction with filtering and zooming for further analysis (a) first time filter and (b) second time filter

We utilize the elbow method to determine the optimal number of clusters for the dataset, as demonstrated in Figure 5. When K = 1, SSE is the largest. The value of SSE decreased when K increased. This means that data processing and partitioning results will be more accurate the bigger K is. However, when K increases to a certain value, the accuracy no longer increases significantly. In this case, we could choose K=4, where the relative improvement is not very high after this point.

For data collection methods, as shown in Figure 6, we have tried a different number of clusters, 20 clusters, and 100 clusters. As described in subsection 2.1., the network is modeled based on two algorithms for data collection purposes, clustering, and tree-based routing. The BS is at the center of the square sensing area. In intra-cluster communications, all non-CH sensors send data to their CHs. Then, the inter-cluster communications, based on the tree that connects all the CHs, collect data from the CHs to be sent to the BS.

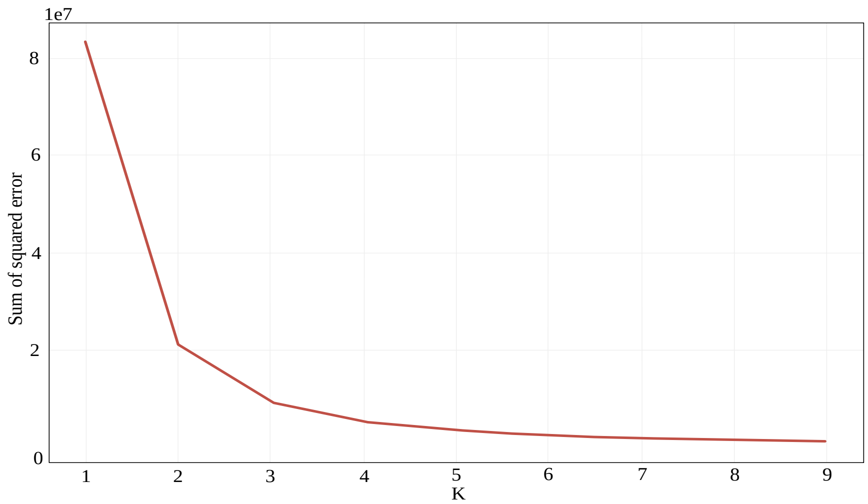


Figure 5. Elbow method for determining the optimal number of clusters

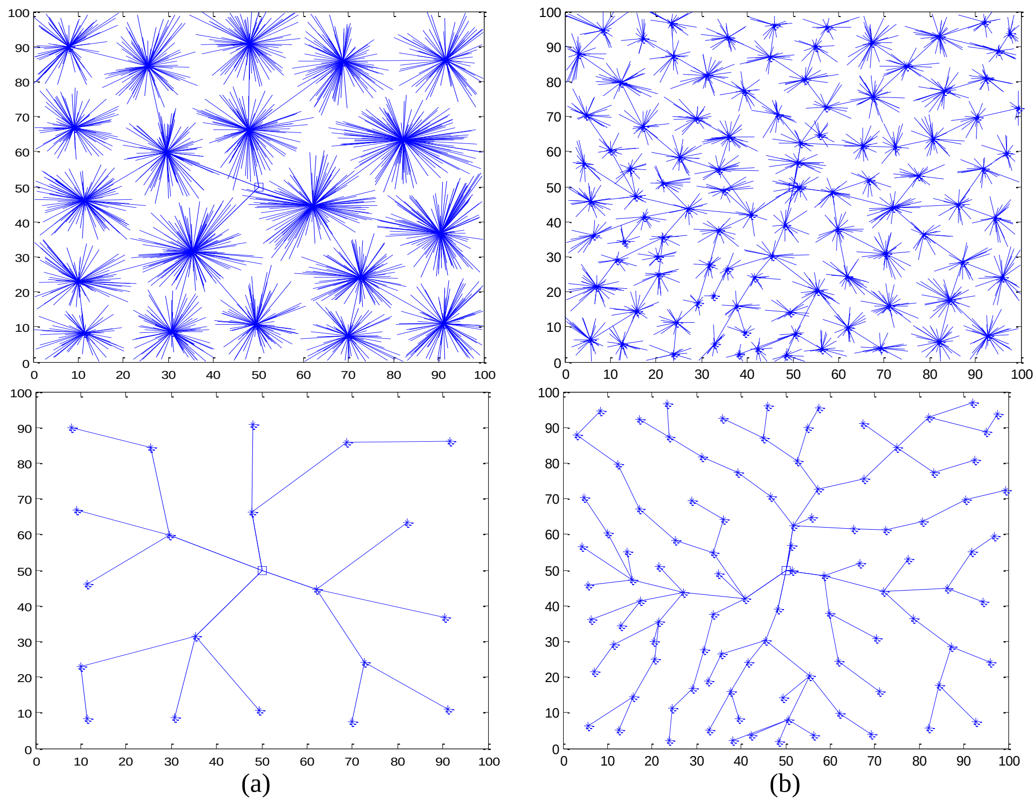


Figure 6. Illustration of intra-cluster and inter-cluster data collection and K-means clustering with diferent number of clusters (a) 20 clusters and (b) 100 clusters

4. DISCUSSION

The current trend of scientific research in the world is the application of human intelligence to analyze, processing as well, and forecast the behavior of things in the surrounding world. This section considers two aspects: i) the potential of data visualization techniques on the empirical application; ii) the challenges and opportunities in implementing the early natural disasters warning system; and iii) the energy efficiency for WSNs based on DV techniques.

The nature of data visualization is also based on the human cognitive system, which tends to be more efficient when recognizing information represented visually. Hence, it plays a vital role in exploiting big data rapidly and effectively in real time through interactive elements and new visualizations. Thanks to the significant benefits such as better analysis, quick action, identifying RoIs, and grasping the latest trends, this technology can be deployed in several applications that directly affect decision-making and even change organizations. However, one of the remaining challenges for the data visualization technique is scalability for big data. In addition, choose the appropriate format to ensure that the content presentation is the most reasonable. Users need to choose suitable technologies, such as machine learning, and artificial intelligence, to meet the requirements to explore the big data sources used for the data visualization techniques.

In recent years, complex happenings of weather have created unpredictability of extreme weather events. This required the warning system to work more professionally to capture weather changes promptly. The system should also focus on communicating infrastructure to share real-time disaster management information. An example of such use cases is incorporating the resulting sensor data visualization to a more extensive, comprehensive dashboard for monitoring, such as with geological aspects, as demonstrated in Figure 7. The sample geolocation data is retrieved from VAST challenge 2019 [30]. Sensor readings for each location are visualized and supported with interactive features, such as filtering and zooming, for monitoring and exploratory tasks.

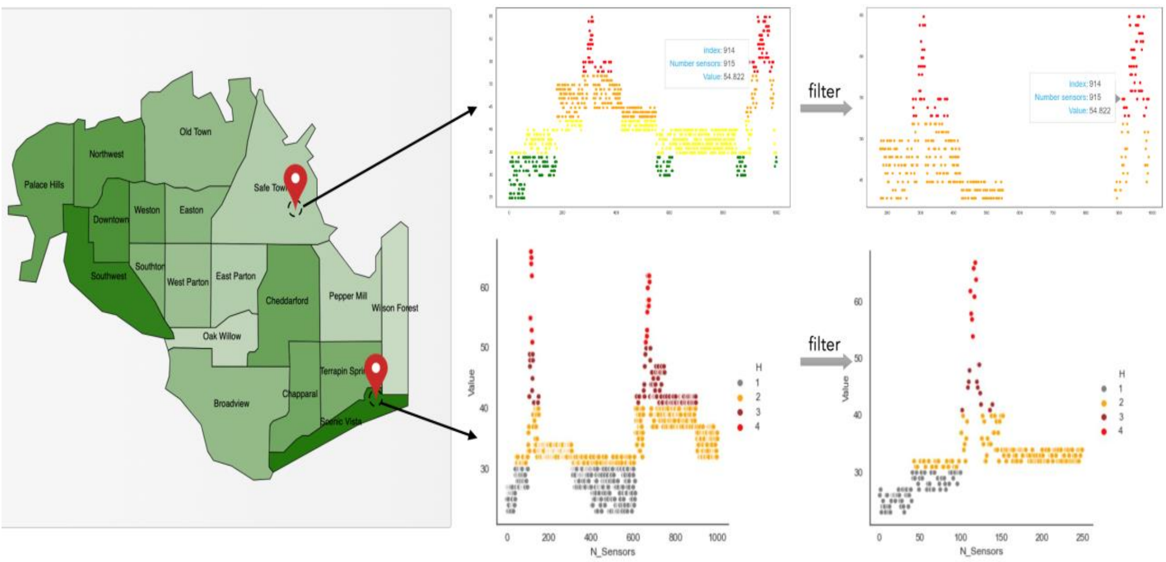


Figure 7. Incorporation of sensor data visualization with corresponding simulation geolocation data

Regarding the energy efficiency for WSNs based on DV techniques, the proposed method can support the WSNs to recognize sensor nodes in the warning areas. Hence, only the sensors communicate with each other and the base station (BS) to forward their data. The other nodes from the network can save energy for other functions. This can save significant energy consumption for all sensor nodes. This also reduces the burden of big data transmission that may cause latency or packet loss in the network communication.

5. CONCLUSIONS

This paper proposes a new model of the natural disaster warning system with data visualization technology to optimize the warning systems in general. This system promptly recognizes significant signs of disasters, such as floods, wildfires, earthquakes, etc., to provide warnings in advance. Sensing data is observed to be processed with data visualization techniques that provide more efficient results. The simulation results describe the data processing and filtering to show RoIs with different priorities to ensure prompt and mitigate high risk. This work shows good points for being able to deploy in practical fields. In addition, the WSNs can only send essential data from sensors in the warning levels. Based on that, the networks can save energy consumption and also can prolong the network's lifetime. Some challenges and opportunities are also identified to develop efficient and reliable warning systems and DV technology. In the future, machine learning and natural language processing can cooperate to reveal significant insights from big data. Thereby, this system can improve to deploy in practice.

ACKNOWLEDGEMENTS

The authors would like to thank Thai Nguyen University of Technology, Viet Nam for the support.

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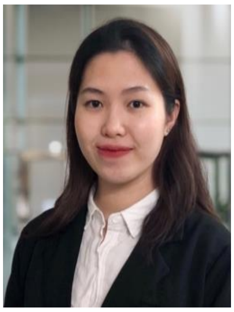
BIOGRAPHIES OF AUTHORS

Assoc. Prof. Dr. Minh T. Nguyen received his B.S., M.S. and PhD degrees in Electrical Engineering from Hanoi University of Communication and Transport, Hanoi, Vietnam in 2001, Military Technical Academy, Hanoi, Vietnam in 2007, Oklahoma State University, Stillwater, OK, USA, in 2015, respectively. Dr. Minh Nguyen is currently the director of international training and Cooperation center at Thai Nguyen University of Technology, Vietnam, and also the director of Advanced Wireless Communication Networks (AWCN) Lab. He has interest and expertise in a variety of research topics in the communications, networking, and signal processing areas, especially compressive sensing, and wireless/mobile sensor networks. He serves as technical reviewers for several prestigious journals and international conferences. He also serves as an Editor for Wireless Communication and Mobile Computing journal and an Editor in Chief for ICSES Transactions on Computer Networks and Communications. He can be contacted at email: nguyentuanminh@tnut.edu.vn.

Cuong V. Nguyen was born in 1987 in Thai Nguyen, Viet Nam. He received his B.S degrees in Electronic and Telecommunication Engineering from Thai Nguyen university of technology and M.S degrees in Electrical Engineering from Hanoi University of Science and Technology. He is a lecture at Thai Nguyen University of information and communication technology. He can be contacted at email: nvcuong@ictu.edu.vn.



Huyen N. Nguyen is a Ph.D. Candidate in Computer Science at Texas Tech University, Lubbock, TX, USA, where she is a member of the interactive Data Visualization Lab (iDVL). Having a great interest in interactive data visualization and visual analytics, she develops visualization systems to support data insight discovery and exploration, especially for time-series and text data. Her visualization research has won recognitions in visualization competitions, such as IEEE Visual Analytics Science and Technology (VAST) Challenge, Bio+MedVis Challenge, and has appeared in EG/VGTC Conference on Visualization and Environmental Earth Sciences. Her work has been funded by the National Aeronautics and Space Administration (NASA) for interdisciplinary research in visualizing qualitative data for science and education. She can be contacted at email: huyen.nguyen@ttu.edu.