Smart City Architecture for Noise Pollution Mitigation through the Internet of Things

Abdulaziz Almehmadi

University of Tabuk, Tabuk, Saudi Arabia

Summary

As most of the world population live in cities with over 60% increase in population in 2030 presenting major challenges related to noise pollution that leads to health concerns, there is a demand for a smart solution that mitigates noise pollution in cities before it reaches dangerous levels. In this paper, we propose a smart city architecture through the internet of things (IoT) to mitigate noise pollution. Mitigation includes the detection and reporting of affected areas and the prediction of possibly affected areas in a city. To evaluate the proposed architecture, we designed Noise Pollution Monitoring System (NPMS) that locates the areas, the time, the level of noise and any related events in the area to provide intelligence throughout applying data mining techniques. Intelligence includes determining if a city is suffering noise pollution, frequent locations where noise pollution needs to be mitigated and the time typically noise pollution occurs in correspondence with nearby occurrences e.g. rush hour, or reported incidents (events) in the city local news agencies. We designed noise pollution detection endpoints that can be deployed at certain locations to collect information including location, time and sound volume. We deployed the endpoints at two major intersections to collect noise levels in order to detect if an area suffers noise pollution and then utilized Support Vector Machine (SVM) and Random Forest classifiers to create a model of prediction of noise pollution before it occurs. Finally, we report the validity of prediction algorithm as well as the functional system.

Key words:

Smart Cities; Internet of Things (IoT); network architecture; data analysis; Wireless Sensor Network (WSN).

1. Introduction

The Forrester research center defines a smart environment as an “environment [that] uses information and communications technologies to make the critical infrastructure components and services of a city’s administration, education, healthcare, public safety, real estate, transportation and utilities more aware, interactive and efficient [1]”. A smart environment can be achieved by utilizing the Internet of Things (IoT). IoT is a system of interrelated computing devices, digital machines and objects that are connected over a network without requiring human-to-human or human-to-computer interaction. IoT assists in designing solutions to major problems such as noise pollution, where end points are connected and provide valuable data that allow for mitigating problems.

Smart city is an urban development vision to integrate Information and Communication Technology (ICT) and IoT technology in a secure manner to manage city's assets and provide poor urban planned cities the ability to overcome many challenges that they may encounter such as noise pollution.

Noise pollution is the disturbing noise with harmful impact on the activity of human or animal life. The source of outdoor noise worldwide is mainly caused by machines and transportation systems, motor vehicles engines and trains. Noise pollution if not managed and mitigated affects cities. Major health problems may arise as a result of noise pollution including cardiovascular effects in humans, increase the risk of death, and contribute to permanent hearing loss [2]. According to [3], noise pollution is usually a result of poor urban planning.

With the increase of population by the end of 2030 with 60% increase of population, noise pollution presents major challenges. In this paper, we propose a smart city architecture for noise pollution though the internet of things. The architecture assists cities to overcome the poor urban planning by identifying if a city suffers noise pollution, the locations where noise pollution needs to be mitigated as well as the time noise pollution usually occurs.

Further, we evaluate the proposed architecture in real world deployment by designing and deploying endpoints that measure noise levels, report location and time when noise levels exceed 87dB. According to the Control of Noise at Work Regulations by the Health and Safety Executive (HSE) in England, “the limit of daily or weekly noise exposure is 87 dB or one peak sound pressure of 140 dB [4]”.

The main objective of the paper is to propose and evaluate a smart city architecture to mitigate noise pollution through IoT which detects and predicts affected areas throughout applying data mining techniques.

The rest of the paper is organized as follows. In Section 2, the related work is provided. In Section 3, the smart city noise pollution architecture through IoT is presented. In Section 4, Noise Pollution Monitoring System (NPMS) is provided. In Section 5, the deployment and data analysis are presented. In Section 6, the results are given. Finally, a prognosis of the future of noise pollution mitigation through IoT is drawn in Section 7.

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2. Related Work

Previous work investigated the noise pollution problem with various approaches some by designing better sensors and others by providing data for future analysis all of which contribute in detecting noise pollution.

The authors in [5] developed a new algorithm to monitor noise pollution that is adapted to resource-constrained devices using wireless sensor networks. The authors developed a new way of mapping noise pollution by using frequency-based algorithms. The results show the effectiveness of the algorithm with difference between the proposed method and the traditional techniques by less than 2 % (1.2 dBA).

Further, Wessels and Basten [6] designed five aspects of acoustic sensor networks for environmental noise monitoring including hardware costs, scalability, flexibility, reliability and accuracy. The aspects led the researchers to creating four categories: a. Networks based on dedicated monitoring equipment, b. Acoustic sensor networks with improved properties with mid-range priced components. c- Low cost acoustic sensor networks for pervasive use and d- Acoustic sensor networks based on smartphones. The four categories contribute to the field of noise pollution monitoring by addressing some of the challenges.

Furthermore, Moukas et. al. [7] provided improved instrumentation that identifies sound sources. The results suggest that application of statistical pattern recognition to recorded sounds can differentiate sources which are structurally dissimilar like trains, fixed-wing, aircraft, and helicopters with an accuracy of 95 percent which assists in identifying noise pollution sources.

A related work done by Siregar et. al. [8] combined multiple sensors in one device utilizing wireless sensor networks to evaluate pollution levels such as dust particle density in the air, humidity, light intensity and the level of noise. The aim of the research is to provide data samples regarding various pollution sources for the research community to analyze. Similarly, the authors in [9] designed a noise pollution measurement system using wireless sensor networks to mitigate the noise pollution problem.

Moreover, the authors in [10] developed nodes to monitor different environments which were composed System-on-Chip (SoC) integrated low-power bluetooth smart transceiver, multi-functional sensor array to monitor environmental parameters, and energy harvesting module that makes the nodes able to adapt and collect energy from solar power, ambient radio waves, and direct wireless power transmission. The result is a new concept of internet of things providing a massively-deployable method to monitor environment in order to gain statistically significant data over a wide area at any time.

Also, Noriega-Linares et. al [11] developed a prototype of a low-cost acoustic sensor based on the Raspberry Pi platform in order to provide a system to analyze the surrounding sounds. The device is connected to the cloud to share results in real time. The computation resources of the Raspberry Pi allow for treating high quality audio for calculating acoustic parameters. In the deployment, the evaluation of these devices through long-term measurements was carried out, obtaining several acoustic parameters in real time for its broadcasting and study. The test has shown that the Raspberry Pi is a powerful and affordable computing core of a low-cost devices while further studies incorporated the power of smartphones to detect noise pollution [12 ,13 and 14] instead of relying on standalone fixed endpoints.

The authors in [15] developed a smart IoT based system for vehicle noise and pollution monitoring to detect and report noise levels and vehicle pollution levels and the authors in [16] provided an open platform for distributed urban noise monitoring that can be utilized in developing smart cities.

The above related work shows the potential and capability of noise pollution detection and monitoring yet missing a smart city architecture for noise pollution mitigation in poorly urban planned cities. In this paper, we propose a smart city architecture to mitigate noise pollution through IoT and design noise detection end nodes as part of the Noise Pollution Monitoring System (NPMS) to evaluate the architecture. In the next section, the architecture is proposed and explained.

3. Proposed Architecture

The proposed smart city architecture for noise pollution mitigation through IoT is depicted in Figure 1. The architecture is composed of three main levels as follows:

3.1 Sensing Layer

The sensing layer is responsible for gathering and pre-processing of data including sound volume, location and time as well as reported events from local news in the tested city.

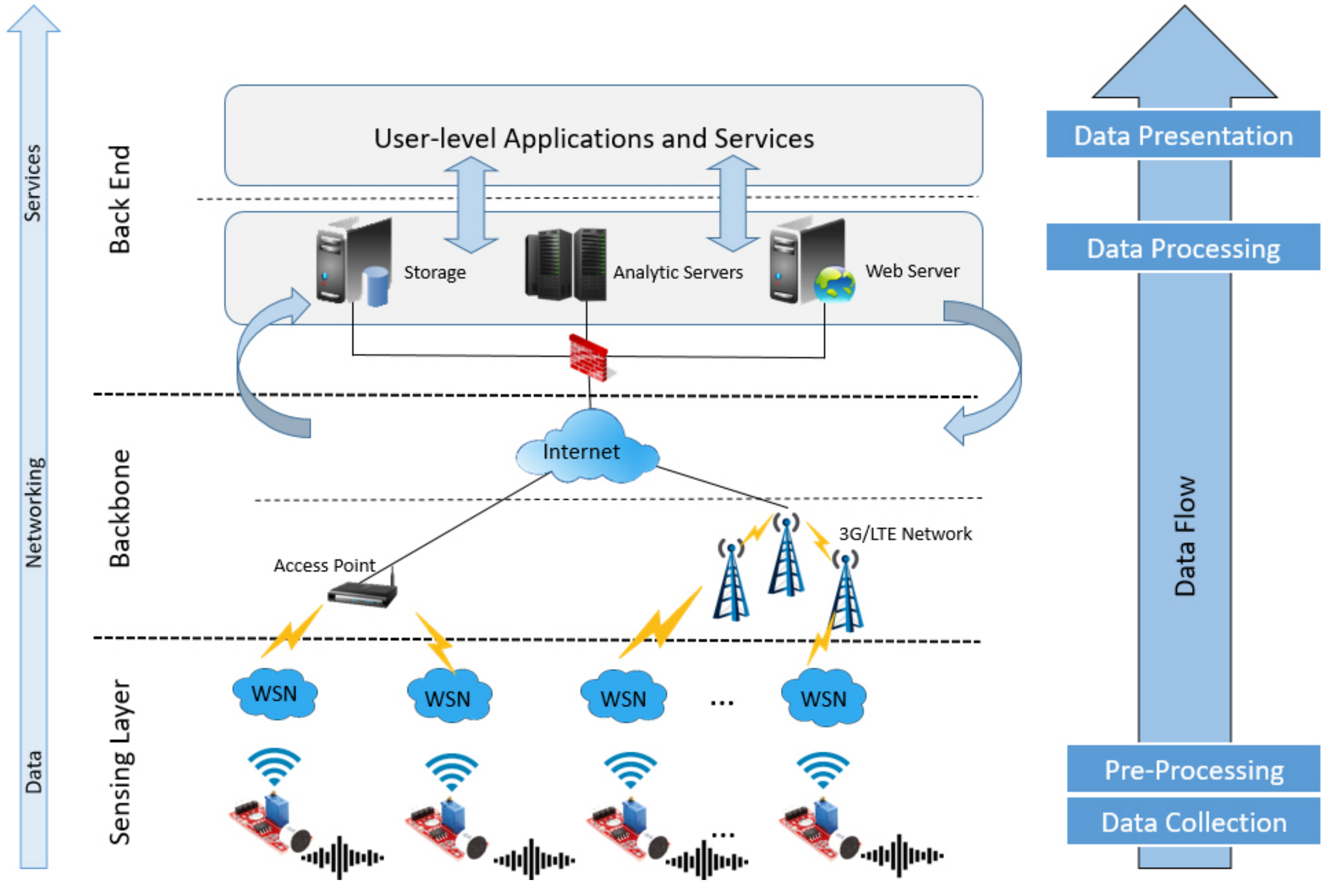

Fig. 1 Smart City Architecture for Noise Pollution Mitigation through IoT.

The layer is also responsible for initiating connections between neighbor nodes through wireless sensor network (WSN). Further, the sensing layer manages reporting non-active nodes for repairing or replacing. Nodes are not based on fixed location but circulate to cover wide areas and predicted areas.

3.2 Backbone Layer

The backbone layer is responsible for transferring the data between nodes and to the Backend Layer and vice versa. The backbone layer may treat crowdsourced nodes as a medium of connection if a node fails to communicate by utilizing RFID technology as crowdsourcing/ crowdsensing in detecting noise pollution has become an effective method for mitigating noise pollution [17, 18, 19 and 20].

3.3 Backend Layer

The backend layer is divided into two levels: 1) the low level which is the main level where data is stored, processed and accessed by operators. It is also where data analysis is done and prepared for the high level and 2) the high level which is mainly where user-level applications and services are provided. The interaction between the nodes and the services is also done in the backend layer for live data streaming and reporting.

4. System Design

To evaluate the smart city architecture in its ability to overcome poorly urban planned cities to mitigate noise pollution, we designed Noise Pollution Monitoring System (NPMS). NPMS is composed of three layers similar to the proposed architecture:

4.1 The Sensing Layer

The sensing layer is composed of a SOC (System on Chip) utilizing windows 10 IoT core, GPS shield, Adafruit Ultimate GPS HAT for Raspberry Pi with an antenna, a sound sensor, Adafruit Electret Microphone Amplifier - MAX4466 with Adjustable Gain, and GSM module. Two nodes are designed for the data collection and pre-processing. Data is pre-processed by removing any abnormal signal that deviates in a 200 ms window.

4.2 The Backbone Layer

The backbone layer is mainly working through the GSM system architecture receiving data from the node through the Base Transceiver Station (BTS) to the Base Station Controller (BSC) and forwarding the data to the backend layer.

4.3 The Backend Layer

The backend layer is composed of three servers: a) storage server, b) analytic server and c) web server.
The storage server receives and records the data from the nodes and then forwards the data to the analytic server. The analytic server receives the data and starts the processing. Any sound volume in a window of 10 seconds above 87dB is considered a noise alert. Any number of alerts in a location that exceeds 6 continuous alerts for a total of 1 minute triggers a warning that is passed to the web application and to the high level of the backend layer where the system administrator is alerted on a location where noise pollution is taking place. A report is then generated and passed to the city council to take an action. Further the analytic server creates a classifier that predicts when noise pollution may occur by analyzing the historical data that is stored in the storage server that includes noise level, location, time and number of alerts in correspondence with nearby events.
The analytic server algorithm is depicted in Figure 2 and the noise prediction algorithm is depicted in Figure 3.

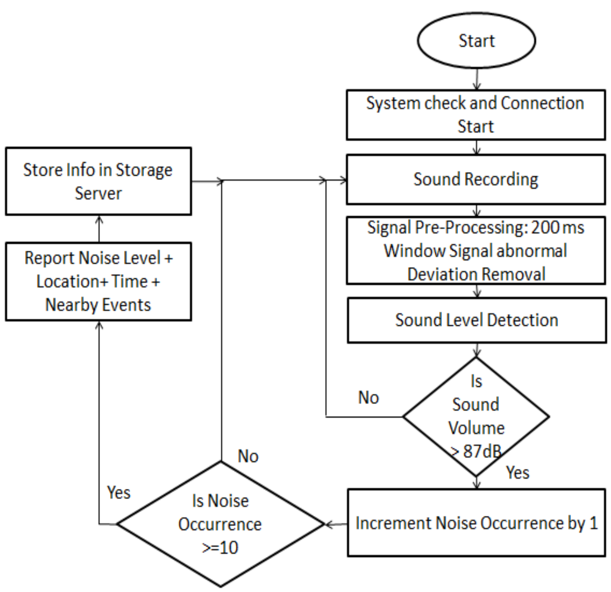

Fig. 2 Noise Pollution Monitoring System Processing Algorithm.

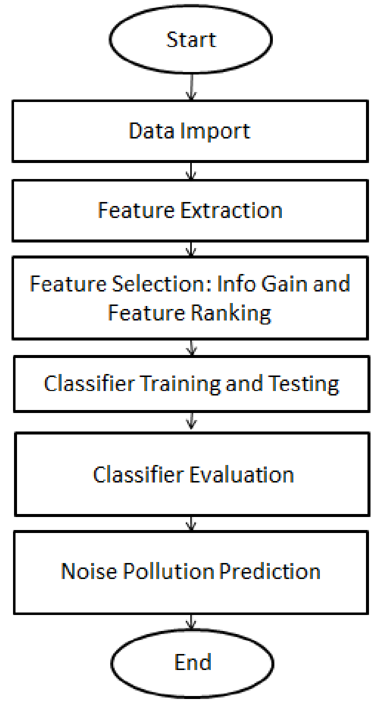

Fig. 3 Noise Pollution Prediction Algorithm.

5. Deployment and Data Analysis

The deployment of the NPMS is done in two areas. The first sensor is placed on a traffic light in a major intersection. The second sensor is placed on a traffic light in another major intersection. In both deployments, we measure the noise level for a period of one month. In both deployments, the systems collect the sound volume and apply pre-processing of the signals to report noise levels when they exceed 87dB for a period of 1 minute as depicted in Figure 2. Also, both systems report the location, time and nearby events. The nearby events are added to each alert by monitoring local news agencies through their twitter accounts.
The data analysis serves two goals of the paper 1) reporting the affected areas and 2) predicting the possibility affected areas in a city.
For the first goal, reporting the affected areas, we locate the area where noise pollution occurred, the frequency of occurrences and the time noise pollution occurs. Then, we plot the affected areas live and provide the system and data to the city to apply techniques of reducing noise levels e,g, posting signs. Data includes determining if a city is suffering noise pollution, frequent locations where noise pollution needs to be mitigated and the time typically noise pollution occurs in correspondence with nearby occurrences e.g. rush hour, or reported incidents (events) in the city local news agencies.

For the second goal, predicting the possibly affected areas in a city, we hypothesize that noise pollution can be predicted by analyzing the history of sound levels in a certain location taking into consideration the local events in that location. For testing the hypothesis, we collected the data and analyzed it by importing the data and extract features from the sound signals, apply the feature selection technique: info gain with feature ranking in order to utilize only the best features. Further, we train Support Vector Machine (SVM) and Random Forest classifiers by using 10 folds- cross validation on the major intersection and then validate the model by applying the data of the second major intersection. We then report the models accuracy levels in their ability of predicting noise pollution in an area before it occurs.

6. Results

After running the system for a period of 30 days in two major intersections in the downtown of the city of Tabuk, we noticed that usually at 8 am, 2 pm and 10 pm noise levels arise, except on March 16, 2018 noise level increased suddenly at 7 pm at one location. Most noise levels were a result of rush hour; however, on March 16, 2018 the local news reported an accident due to traffic light malfunctioning. Figure 4 depicts the noise levels on two days in March where each peak is an increase in noise levels that indicates an incident in that location if it is sudden or a frequent noise peak that requires attention from the city. The noise levels for the 16th day of March 2018 show four peaks at 8 am, 2 pm, 7 pm and 10 pm, and the usual noise levels for the 17th day of March showed three peaks at 8 am, 2 pm and 10 pm. Most days showed three peaks at around the same time except for abnormal incidents that show higher than normal peaks at unusual times.
Further, for testing the hypothesis that states, noise pollution can be predicted by analyzing the history of sound levels in a certain location taking into consideration the local events in that location, we analyzed the noise levels per second before a peak occurrence taking into consideration the location, the frequency of peaks in certain days, the time and any local event taking place in that location as features to predict noise levels before they happen. We analyzed the 4 hours before a noise pollution occurred in comparison to the same 4 hours when no noise pollution occurred. The noise pollution that occurred at 8 am is a result of rush hour; therefore, we compared the data with sound levels at 4,5,6, and 7 am on the weekends where no rush hour existed, and no noise peaks existed as well.

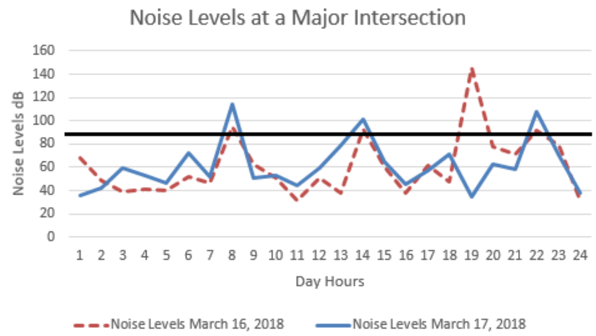

Fig. 4 Abnormal vs. Normal Noise Peaks in a Major Intersection.

A two-tailed paired samples for means t-test uncovers that the sound levels before noise pollution occurs (M=39.45, SD=10.14) compared to the sound levels that are not followed by noise pollution levels (M =62.15, SD=12.30, $p \leq .0001$.
Analysis of Variance (ANOVA) also suggests a difference between the sound levels before noise pollution occurs and sound levels that are not followed by noise pollution $p < 0.0001$. The statistics support the hypothesis of detecting noise pollution before it occurs $P < 0.0001$.
Furthermore, the SVM classifier reported 100% accuracy in detecting a peak before it occurs when training the classifier with the noise pollution levels before a peak of noise pollution occurs and when no noise pollution occurs. The Random forest classifier reported 96.81% accuracy. Moreover, we applied both classifiers on the data that was recorded at the second major intersection and the SVM classifier reported 97.47% accuracy where Random forest classifier reported 89.1% accuracy in predicting if noise pollution will occur in the next hour or not.

7. Conclusion and Future Work

In this paper, we proposed a smart city architecture for noise pollution mitigation through IoT. We further evaluated the proposed architecture by designing Noise Pollution Monitoring System (NPMS) and deployed the endpoints at two locations. The system and data showed promise in detecting and reporting noise pollution allowing for providing the information through a web application to the city to mitigate frequent locations where noise pollution occurs. Furthermore, we hypothesized that we can predict noise pollution before in occurs by analyzing the sound levels before noise pollution occurs and the sound that is not followed by noise pollution. The statistics supported the hypothesis and the classifiers showed 97.47% and 89.1% ability to classify sound levels that are and are not followed by noise pollution for the classifiers SVM and Random forest respectively. Further research is required by deploying multiple endpoints throughout a city and utilizing the mobility of microphones through smartphones and crowdsourcing in order to detect and prevent noise pollution.

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Abdulaziz Almehmadi received the Bachelor's degree in computer science and the Master's degree in information technology security, with a specialty in biometrics, from King Abdulaziz University, Jeddah, Saudi Arabia, and the University of Ontario Institute of Technology (UOIT), Oshawa, ON, Canada in 2007 and 2010 respectively. Dr. Almehmadi received his PhD in computer science from UOIT in 2015 with a specialty in biometrics and access control. His thesis work was submitted to the United States Patent and Trademark Office (USPTO) and was granted the patent US9703952 in July 11, 2017 titled: Device and Method for Providing Intent-based Access Control. Dr. Almehmadi is currently working on designing non-identity-based access control systems to detect and prevent insider threats. He is an assistant professor at the Information Technology department at the Faculty of Computing and Information Technology (FCIT) at the University of Tabuk, Saudi Arabia. He is also the Vice-Dean for Graduate Studies and Scientific Research at FCIT. Furthermore, Dr. Almehmadi has recently founded and is the Director of the Industrial Innovation and Robotics Center (IIRC) at the University of Tabuk with projects to support the NEOM SmartCity.