NOISE POLLUTION MONITORING

Consider incorporating data analytics to identify noise pollution patterns, high-noise areas, and potential sources.

ABSTRACT :

The proposed noise monitoring system consists of smart sensors connected to cloud services via wireless uplinks. Figure 1 shows an overview of the system. The intelligent sensor consists of a single-board computer with a measurement microphone and a wireless transmitter unit. To alleviate privacy concerns associated with continuous audio capture and storage, most of the analysis and processing already occurs within the sensor, and by default only analyzed data is transmitted and stored. This approach also reduces the amount of data sent from the sensor to the cloud service, allowing the sensor to be placed in areas with poor quality wireless uplinks. The sensor continuously calculates A-weighted 10-minute equivalent sound pressure level values and detects noise sources prevalent within the measurement period. This information is used to determine whether a real acoustic signal is required for further testing on the cloud service. For example, segments that exceed the maximum legally permissible sound level can be saved for manual inspection. All extracted measurements are transferred from the smart sensor to a cloud service for further analysis. The cloud service stores data in a measurement database, and audio segments marked for later review are stored on a disk server. End users access measurement data and analysis through a web-based portal.

KEYWORDS:

Environmental noise monitoring ; Acoustic pattern classification ; Wireless sensor network ; Cloud service

Data analytics can be utilized in noise pollution monitoring systems to identify patterns, high-noise areas, and potential noise sources**.**

1. **Data Collection**: Smart sensors continuously collect noise data and send it to a central database or cloud platform, which usually includes time-stamped noise**.**

2. **Data Pre processing:** Data pre processing techniques, such as noise filtering and data imputation, can assist in removing outliers, inconsistencies, or missing values from raw noise data.

3. **Noise Level Analysis:**
   Time-series analysis is a method for analyzing noise data to identify daily, weekly, or seasonal patterns in noise levels. This can be beneficial.
   Spatial analysis can reveal high-noise areas by aggregating noise measurements within specific geographic regions. A heatmap can be used to visualize the data.
   Frequency domain analysis can help distinguish different types of noise sources based on their spectral characteristics. For exams.

4. **Anomaly Analysis**: Data analytics is capable of detecting noise events that are unusual or anomalous. Sudden spikes in noise levels that exceed typical patterns can be detected
5. **Source Identification:** Advanced analytics, including machine learning algorithms, can be employed to identify potential noise sources. These algorithms can learn from historical data and make predictions about the likely sources of noise based on their characteristics.

6. **Correlation with environmental factors**: It is possible, and noise data can be correlated with other environmental factors like air quality, temperature, and humidity.

7. **Predictive modelling**: It has the potential to develop predictive models that predict future noise levels based on historical data and external factors.

8. **Visualizations and Reporting**: Data analytics results can be visualized through charts, graphs, maps, and reports, and dashboards that are user-friendly can also be utilized.

9. **Alerting and Notifications**: When noise levels exceed predefined thresholds or when potential noise sources are identified, the system can send automated alerts and notifications to relevant stakeholders, such as local authorities or environmental agencies

10. **Continuous improvement**: Data analysis can be used to evaluate the effectiveness of noise reduction measures and policies over time. This feedback loop enables data-driven decision-making and continuous improvement efforts. By integrating data analytics into noise pollution monitoring systems, you can go beyond just monitoring noise levels to gaining deeper insight into the sources, patterns, and impacts of noise pollution. This information can inform policy-making, urban planning, and noise mitigation strategies to create quieter, more livable environments.

NOISE MONITORING:

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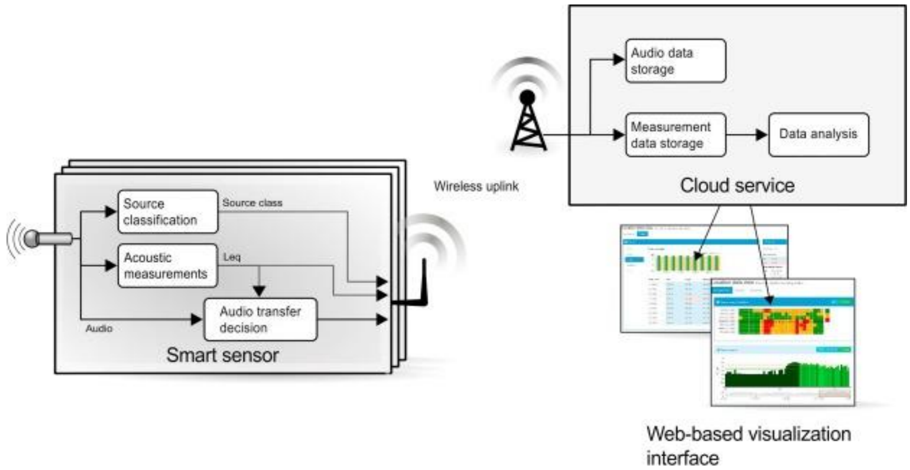


Fig. 1. Block diagram of the noise monitoring system.

ACCESSING DATA AND VISUALISATION:

Measurements are accessed through a web-based interface that uses data visualizations and data reports to summarize large numbers of measurements in an easy-to-read format. Sound pressure level (SPL) measurements can be filtered based on sound source classification results to display measurements related to specific sound sources. The service visualizes measurement data in a variety of ways, including calendar heatmaps, graphs, and reporting tables. An example of the portal view is shown in Figure 2..

Fig. 2. Example view of the noise monitoring portal

In the top right corner there is a calendar selector for day view. Select a day to see detailed data for that day in the calendar view and graph view on the left. The measurement calendar shows the measurements associated with the target source, and the graph view shows the presence of the target by color intensity. Audio playback will appear in the bottom right corner.

Calendar heatmaps are used to visualize the average SPL values over a period of time (1 day, 1 hour) with the colors of the calendar cells. An example of this is shown in Figure 2 as a measurement calendar. Heatmaps summarize SPL measurements within an hour into a single number and decode them into colors based on site-specific SPL limits. In a preliminary study, it was observed that three colors can adequately visualize the measured SPL values. In this case study, colors are defined as follows: Green indicates sound pressure levels below 45 dB, yellow indicates sound pressure levels between 45 dB and 55 dB, and red indicates sound pressure levels above the outdoor noise national limit of 55 dB. Residential areas. Limit values are subject-specific adjusted according to national legislation. Only measurements assigned to the target sound class are displayed in the calendar.

Measurement charts are used to visualize SPL values compared to measurement timestamps. An example of this is shown at the bottom of Figure 2. Three types of graphs are used to visualize measurements assigned different data. The first displays all SPL measurements as is, and the second displays the SPL measurements and source probabilities for the current time interval, indicated by the intensity of the color below the curve. Third, only the SPL measurements associated with the target sound source are displayed. Site-specific SPL limits for noise monitoring (similar to a calendar heatmap) are shown on the horizontal line graph.

In addition to calendar and graph-based visualizations, use numerical measurement reports to view more accurate values and analysis. Reports are used to display daily, weekly, monthly, and yearly averages of sound pressure measurements. The report also includes noise descriptors such as daytime, evening, and night levels introduced in END [1] to provide a comprehensive representation of noise levels over time. If desired, higher noise values such as undistorted annoyance (UBA) can be added to the calculation.

The portal provides different levels of information depending on the type of user account. Administrators of monitoring sites (system customers) can grant access to people who live near the monitoring site (general users). The service provides easy access to an overview of noise measurements and the ability to add feedback and comments during measurements. Provides direct connection to monitoring site management. Construction managers or community liaisons can use public feedback to address noise levels and types and respond directly to comments. If there is any saved audio associated with the annotated timestamp, site administrators can also listen to it at this stage. Public access is important to make noise monitoring transparent and engage the public by giving them a more active role in interpreting monitoring results. This should reduce many negative attitudes about environmental noise and noise monitoring. For administrative users such as government agencies, it provides accurate measurement reports that help track average noise levels over time and is often used in public noise management.

AUTOMATIC DETECTION OF TARGET SOURCES:

In the proposed automatic target sound source detection system, noise is classified into two classes. Sounds propagating from the target source belong to the target class, while disturbing sounds and silence belong to the background class. Examples of possible target sounds include plant noise and aircraft noise. Possible background noises include traffic, wind, rain, lightning, birds, etc. Target

source activity is detected by analyzing continuous audio input and binary classification between background and target. The audio input is the same signal used for sound pressure measurements, but without the A-weighting filter.

The detection system consists of two stages: the training stage and the monitoring stage (see Fig. 3). Acoustic models are learned from training examples, captured audio with manual annotation, in the training stage. The learned acoustic models are used to classify audio captured on a sensor,

to detect the activity of target, in the monitoring stage. An example of the system output is given in Fig. 4. The training algorithm needs only annotation of target sounds. Traffic sounds, regarded as background in 5 are annotated to help understand the system output

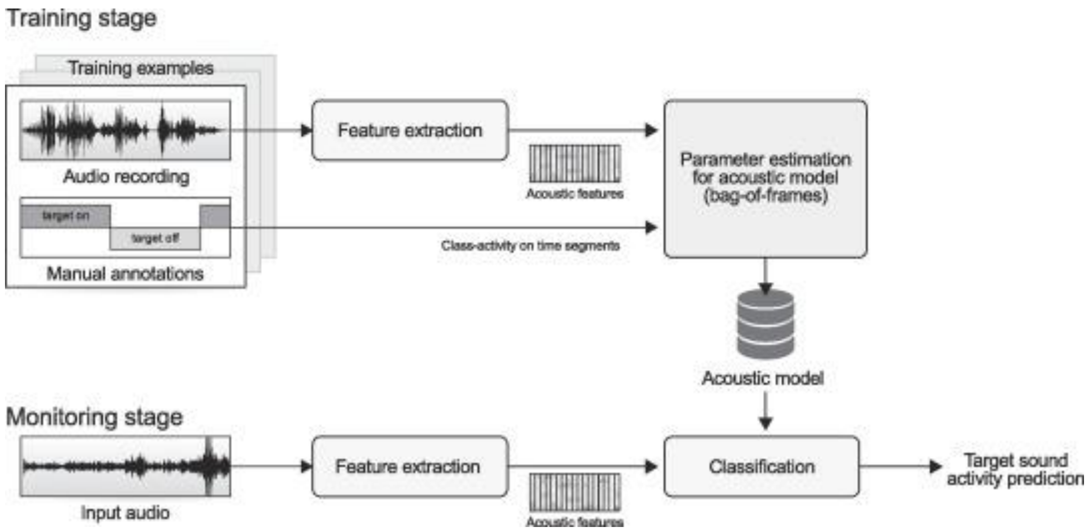


Fig 3.Block diagram of the automatic target sound detection system

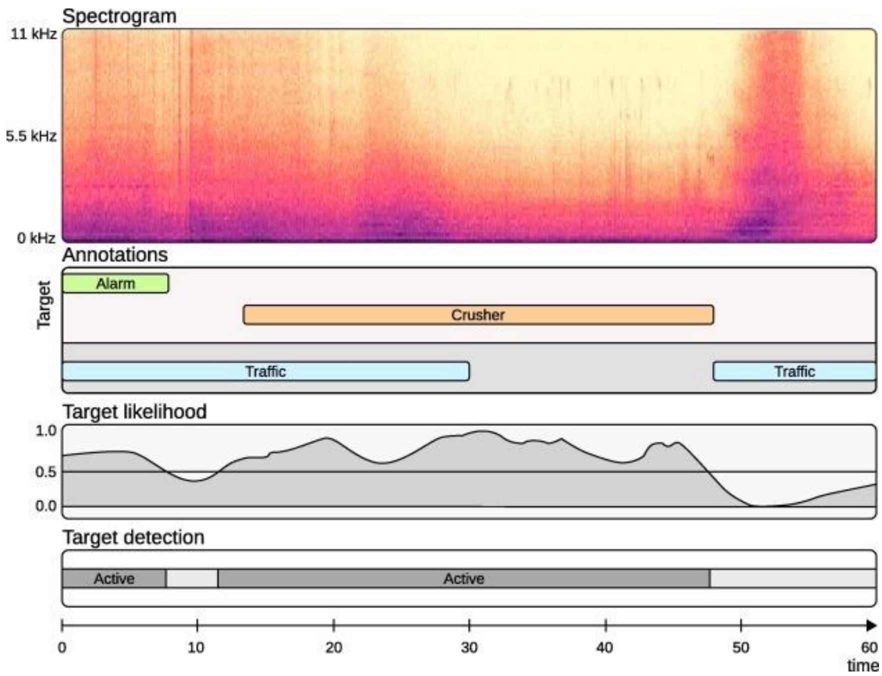


Fig. 4. Example of the target detection output using the GMM classifier

The top panel shows the spectrogram and the second panel shows the corresponding annotation. Traffic is considered background noise, and breakers and alarms are target sounds. The third panel shows the target probability and decision threshold. The recognition results are displayed as system output in the lower panel

Training and monitoring:

Supervised learning requires a set of training examples. H. Audio signal with manual annotations during the training phase. The target class feature vector is derived from the temporal segment annotated as the target sound, while all other frames are used to represent the background class. The extracted features (MFCC) are collected for each class according to the annotations. When GMM is used, the features are used to estimate the feature distribution for each class. When an ANN is used, the target outputs are [1,0] and [0,1] of the feature vectors corresponding to the background and target classes, respectively. During the monitoring phase, non-overlapping segments are detected in seconds. The score for each class is computed as the sum of the log-likelihood (log of the likelihood) for each frame in the corresponding seconds. The target probability in Figure 4 is calculated as the value of the target class divided by the sum of all classes. If the target probability exceeds a threshold (default value 0.5), the target sound source is recognized as active, otherwise it is inactive. If precision is more important than recall, or vice versa, you can adjust the threshold. Precision and recall are discussed later in Section 4.3. Figure 2 shows a noise portal representing the estimated target activity over a long period of time (1 hour). The majority of votes come from the activity output for the corresponding seconds.

CAPTURED NOISE DATA:

Three minutes of audio was continuously captured every 10 min, making a total of 432 min for each day. All types of noise generated by the working activity of the plant was collectively defined as the target class, including rock crushing, lifting-truck sounds, and alarm sounds from the machinery. On the contrary, traffic noise coming from the road and the noise generated by the wind and the trees were two significant types of background sound sources. Example sound spectra of rock crushing, a car passing, and wind is given in Fig. 5.

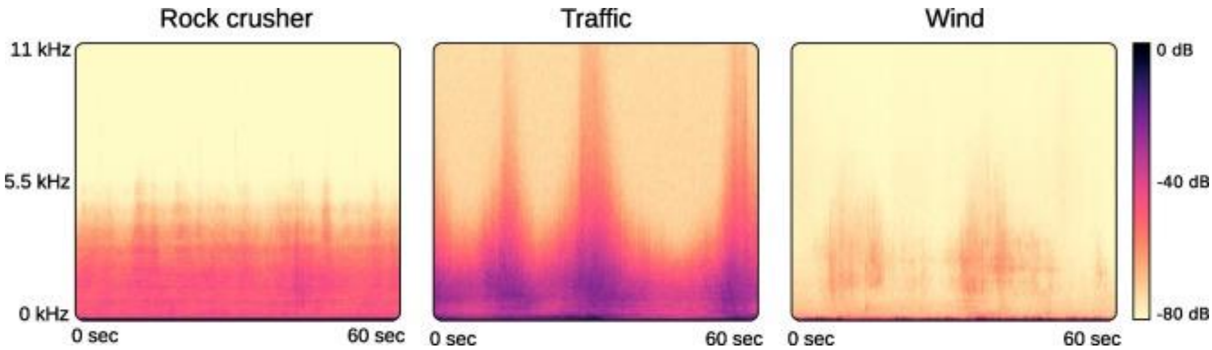


Fig. 5. Example sound spectra for rock crushing, a car passing, and wind from left to right.

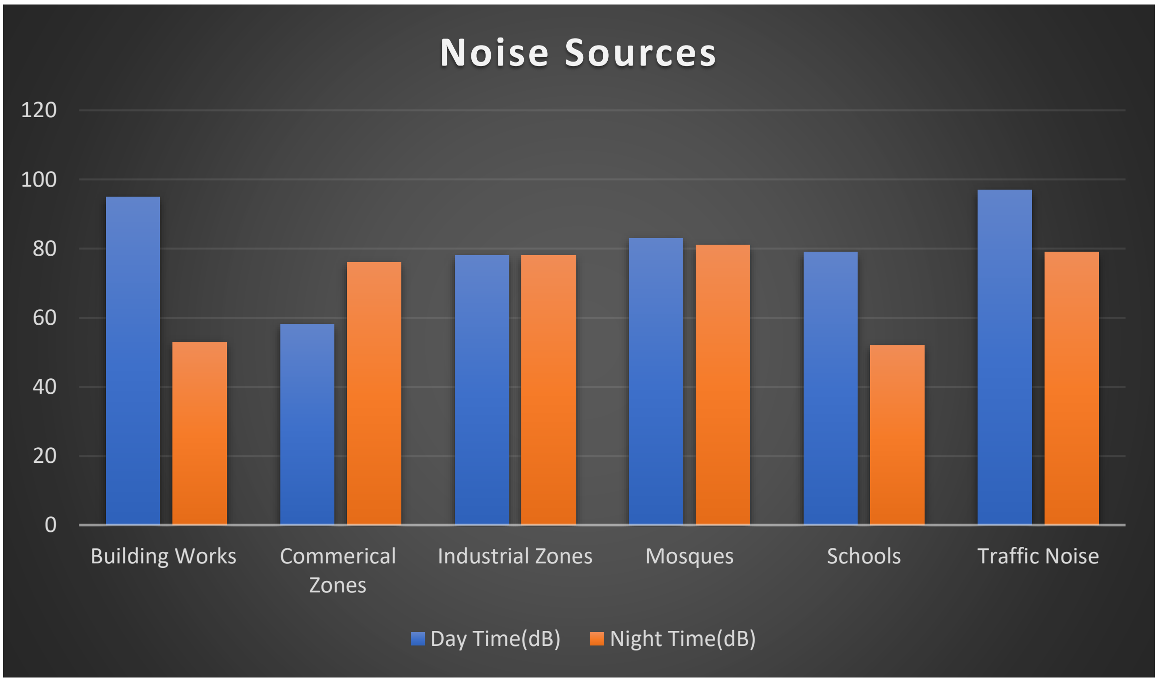
Three minutes of audio were continuously recorded every 10 minutes, resulting in a total length of 432 minutes each day. All types of noise generated by factory work activities, such as rockfall noise, pallet truck noise, and machine alarm sounds, were collectively defined as a target class. On the contrary, there were two important types of background noise sources: traffic noise emitted from roads and noise generated by wind and trees. Figure 5 shows examples of the sound spectra of falling rocks, passing cars, and wind.

SENSOR NETWORK:

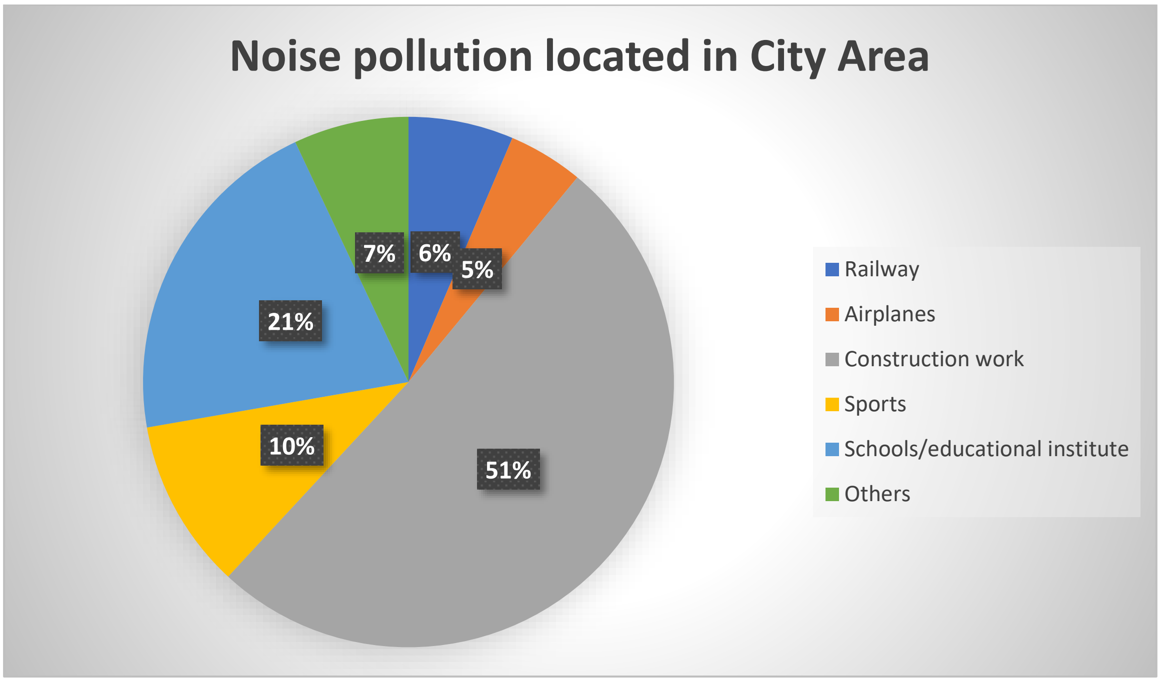
In the future, all data from different network sources, either already available or from autonomous smart sensors, will be centralized in a cloud service, making the data accessible to different groups of people, such as the public, authorities, etc. It will look like this. Avid users. The data can be used for any purpose needed, including mapping and monitoring of emissions, noise, aerosols, etc. It is possible to obtain accumulated standardized descriptors and traditional reports for various purposes. It is also possible to comment on the visualized results and audio results if necessary on the timeline and provide feedback to the person in charge. To increase the effectiveness of classification, multiple sensors can also be used to analyze the direction of sound arrival. The final result of the environmental noise assessment will be a future nuisance map of the area, marked with a level of uncertainty. Furthermore, if requirements exceed current legal values and limits, it is possible to calculate higher level descriptors on the sensor, such as pure noise pollution or other psychoacoustic descriptors. The solar sensor is optimized for average summer conditions, so the battery keeps the system running at night. However, external energy is required during long periods when direct sunlight is limited or non-existent (such as winter north of the Arctic Circle)

Eg:

NOISE SOURCES :



NOISE POLLUTION LOCATED IN CITY AREA:



CONCLUSIONS:

It has been shown that environmental noise monitoring can be improved by separating targets and noise sources and implementing this approach at the sensor level. The implementation of autonomous and cost-effective sensors connected to cloud services was also presented.

The Raspberry Pi, a single-board computer the size of a credit card, has proven to be powerful enough for automatic classification of information sources. Photovoltaic sensors have shown that measurements can be taken even in locations without electrical outlets.

Noise source activity was captured through binary classification between target and background. Mel-frequency cepstral coefficients were used as acoustic features, and classification was performed using supervised classifiers (GMM and ANN) learned from annotated audio recordings. The performance of the developed method was evaluated in a case study of a rock crushing plant. Quantitative evaluation shows that the noise source classification by the proposed approach is sufficiently accurate. At a time resolution of 1 second, an F-score of 0.938 was achieved for the best classifier examined. the system was working

The results of the developed classifier were in good agreement with the normal operating time of a rock crushing plant. Cloud services and Noise Portal were also introduced. The sensors sent the results to a cloud service, and the portal was used for visualizing the results, statistical analysis, and archiving the data. This approach allows the system to scale towards noise management and minimizes the cost per sensor unit, allowing it to scale towards real-time noise mapping measurement data. Using this approach increases the reliability, effectiveness, and spatial coverage of environmental noise monitoring.