# GIS Based Transportation Noise Representation Leveraging Techniques of Deep Learning, Crowd Sourcing and Sound Recognition

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**Abstract :**

Noise mapping on Geographic Information Systems (GIS) is a valuable technique for assessing and visualizing noise pollution levels in each area. By combining noise data with spatial information, GIS enables the creation of comprehensive noise maps that can aid in understanding and managing noise-related issues.GIS platforms provide powerful tools for noise mapping, allowing users to overlay noise measurements onto a digital map. These measurements can be collected from various sources, such as on-site measurements, noise monitoring devices, or predictive models. By assigning noise values to specific locations, GIS can generate contour maps, color-coded heat maps, or 3D representations that highlight noise intensity across the area of interest. Noise mapping on GIS offers several benefits. It helps identify areas with excessive noise levels, facilitating targeted interventions to mitigate noise pollution and improve quality of life for residents. Additionally, it supports urban planning by considering noise impact during the design and development of new infrastructure, ensuring proper land use zoning and reducing potential conflicts between residential and noisy areas. Integrating noise mapping with other spatial data, such as transportation networks or population density, GIS enables a more comprehensive understanding of noise pollution patterns and their associated factors. This information can inform policymakers, urban planners, and environmental agencies to make informed decisions, implement noise reduction strategies, and create healthier and more sustainable environments.

Interpolation mapping using Inverse Distance Weighting (IDW) is a valuable technique for estimating values at unobserved locations based on nearby sampled points. IDW assumes that values closer to a target location have a stronger influence on its estimated value compared to points farther away. The IDW interpolation method assigns weights to the known sample points based on their distances to the target location. The weights are determined inversely proportional to the distance, hence the name Inverse Distance Weighting. Closer points have higher weights, indicating a stronger influence on the interpolated value. In order to perform IDW interpolation, a power parameter is typically chosen to control the influence of nearby points. Higher power values result in a steeper drop-off in influence with distance. Conversely, lower power values lead to a more gradual influence decrease. IDW interpolation can be used for various applications, such as mapping environmental variables like temperature, precipitation, or pollutant concentrations. It is particularly useful when there is limited spatial coverage of data points or when data is unevenly distributed across the study area. In summary, IDW interpolation is a valuable technique for estimating values at unobserved locations based on nearby sampled points. It provides a flexible and intuitive approach for creating interpolated maps, but careful consideration should be given to its limitations and the appropriate choice of parameters.

Noise is a universal problem that is particularly prominent in developing nations like India. Short-term noise-sensitive events like New Year's Eve, derby matches, DJ night, Diwali night (celebration with firecracker) in India, etc. create lots of noise in a short period. There is a need to come up with a system that can predict the noise level for an area for a short period indicating its detailed variations. GIS

(Geographic Information System)-based google maps for terrain data and crowd-sourced or indirect collection of noise data can overcome this challenge to a great extent. Authors have tried to map the highly noisy Diwali night for Lucknow, a northern city of India. The mapping was done by collecting the data from 100 points using the noise capture app (30% were close to the source and 70% were away from the source (receiver). Noise data were predicted for 750 data points using the modeling interpolation technique. A noise map is generated for this Diwali night using the crowd-sourcing technique for Diwali night. The results were also varied with 50 test points and are found to be within ±4.4 dB. Further, a noise map is also developed for the same site using indirect data of noise produced from the air pollution open-sourced data. The produced noise map is also verified with 50 test points and found to be ±6.2 dB. The results are also corroborated with the health assessment survey report of the residents of nearby areas.

Indirect noise mapping using air quality parameters like NOx, SOx, and PM2.5 offers a novel approach to estimate noise levels in an area based on the correlation between air pollution and noise pollution. This technique leverages the understanding that certain pollutants emitted by sources like vehicles or industrial activities contribute to both air pollution and noise generation. In this way by establishing a relationship between changes in air quality parameters and corresponding changes in noise levels during specific periods, it becomes possible to predict the probable percentage change in noise levels due to variations in air pollution levels. In order to implement this approach, data on air quality parameters such as NOx, SOx, and PM2.5 are collected through monitoring stations strategically placed in the study area. These parameters provide an indirect measure of the pollution levels, which are then correlated with recorded noise levels during the same periods. Using statistical methods and data analysis techniques, a relationship or model is developed to estimate noise levels based on the measured air quality parameters. This model can then be applied to predict noise levels in areas where only air quality data is available, without direct noise measurements. This indirect noise mapping technique has several advantages. It offers a cost-effective approach as it utilizes existing air quality monitoring infrastructure and data. It also enables noise predictions in areas where direct noise measurements are challenging or not feasible. However, it is important to note that this approach assumes a consistent relationship between air pollution and noise pollution, which may vary depending on the specific sources and local conditions. Calibration and validation of the model with direct noise measurements are essential to ensure accuracy and reliability. In summary, indirect noise mapping using air quality parameters provides a valuable alternative for estimating noise levels in areas where direct noise measurements are limited. By establishing correlations between air pollution and noise levels, this technique offers insights into noise pollution patterns and aids in decision-making processes related to noise management and urban planning.

The paper discusses the development of a simple location service module for identifying vehicles' characteristics, including their types, speed, and noise, using audio samples recorded on roads. The system utilizes a single unidirectional microphone strategically placed over a two-way road corridor to collect audio samples of running vehicles. The authors used a convolutional neural network-based recognition pipeline that operates on the short-time Fourier transform (STFT) spectrogram of the sound in the log domain to extract three different types of vehicles (Bike, Car, and Truck) with their class and speed by feeding the STFT spectrogram into the algorithm. The technique further helped extract five different categories of noise-sensitive events. The collected audio training data were synced with video data to generate audio-based training samples for location service module extraction. The recorded audio samples were divided into an 85:15 ratio for training and testing. The study used eight classifiers (M-CNN, LSTM, RF, DT,etc) to classify noise events with vehicle type, speed, and noise characteristics. The modified CNN gave the accuracy of vehicle extraction of 88.94%, which is 24.94% higher than classical machine learning and 12.3% higher than deep learning approaches. The speed of extracted vehicles had an overall accuracy of 69%, and the prediction of noise values was found to be within -5 to +4 dB(A). The results suggest that the developed system can offer significant help for transportation control and urban planning by providing accurate and timely information on vehicles' characteristics.