A model for implementing vibration and sound heatmaps in smart cities based on crowdsensing data

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Abstract
This paper aims to establish a model that can utilize vibration and sound heatmaps in smart traffic using Internet of things, mobile and web technologies. The developed system should be able to monitor and collect information using crowdsensing technology, as well as provide the current status of the environment. The final objective of the model is to generate visual heat maps related to perceptual attributes (e.g. 'calm', 'pleasant', 'unbearable') with collected vibrations and sounds as a starting point. The proposed system is developed through these main stages: (1) Vibration and sound sources recognition (2) Profiling of the sources (3) Prediction of perceptual measures divided by the area (4) Implementation of vibration and sound heatmaps. This research is specifically focusing on the last two stages (predictions and implementation). These stages are broken down into smaller phases with methodology and processes described in detail. The model of the developed system was realized through measured vibrations and sound data in urban transportation in Novi Sad city. Finally, we present the research results from the analysis paradigm and provide suggestions for its implementation.

Keywords: sound in traffic, vibration in traffic, smart traffic, environmental noise, crowdsensing

1. Introduction
A smart city is a city that functions in a sustainable and intelligent way, by integrating all its infrastructures and services into a cohesive whole and using intelligent devices for monitoring and control, to ensure sustainability and efficiency [1].

Smart cities promote sustainability and improve people's quality of life and this has been shown to be a crucial aspect of environmental management and sustainable development strategies. Furthermore, it has also been noted that the concept of smart cities is not only focused on technological aspects, and is gradually evolving into a broader idea including components strongly connected to people and community [3].

The sound environment has often been disregarded within this framework, although it is one of the main components of the human experience in urban contexts and is directly related to human health and well-being. Therefore, in recent years it has attracted more and more attention from the computational side [4].

The other disregarded problem is traffic vibrations and their impact on human health and the environment. A daily bus, tram, or train ride can affect a person's mental and physical health. Moreover, if the building is located near a busy street, it can cause damage to buildings due to vibration. The human body is not designed to receive vibrations, so it is necessary to determine the impact of these on human health [5].

Information about the traffic environment is collected using sensors. Sensing is at the heart of any smart infrastructure, which can monitor itself and act on its own intelligently. Using sensors to monitor public infrastructures, such as bridges, roads, and buildings, provides awareness that enables more efficient use of resources, based on the data collected by these sensors. Real-time monitoring eliminates the need for regularly scheduled inspections, therefore reducing costs; measuring energy consumption in households allows for accurate load forecasting; and sensors deployed in roads for traffic monitoring collect data that is necessary for the implementation of intelligent transportation systems (ITS) [2].

Mobile crowdsensing is an emerging paradigm based on the application of sensors and crowdsourcing. The use of mobile device sensors enables the acquisition of local geospatial information and the provision of information. Knowledge sharing with other users and the wider community creates a foundation for mobile crowdsensing [6]. Mobile crowdsensing has been defined as a data exchange and information extraction process, based on the collaboration of individuals with sensors and computing devices, to measure and enumerate phenomena of mutual interest [7].

This paper will focus on data collected using mobile crowdsensing technology. The aim is to establish a model that can utilize collected vibration and sounds data using mobile crowdsensing in the environment.

2. Literature review

There are many areas related to smart traffic that have space for improvement. Many researchers are focusing on traffic noise pollution. In [8], the researchers are focused on the relationship between long-term exposure to traffic noise and mortality. They are doing a systematic review and meta-analysis of epidemiological evidence for a period between 2000 and 2020. In [9], researchers are focusing on finding a connection between accelerated aging and age-related diseases (CVD and Neurological) due to air pollution and traffic noise exposure. They were able to recognize the role of environmental factors (such as air pollution and noise exposure) as crucial determinants of the aging process. In [10], the researchers focused on road traffic noise and cardiovascular disease risk factors in UK Biobank (a company in the UK). They have proven that exposure to road traffic noise >65 dBA, independent of nitrogen dioxide, was associated with small but adverse changes in blood pressure and cardiovascular biochemistry.

Other researchers are using data about traffic noise to make maps and do machine learning predictions. In [11], researchers are developing dynamic traffic noise maps based on noise monitoring and traffic speed data. They developed a new method for dynamic updates of traffic noise maps in large regions based on noise monitoring and traffic speed data, which consists of two parts:

- A model of the noise level and traffic speed is proposed to update dynamically the noise source intensity of the whole road network with the real-time noise monitoring data
- The acoustic attenuation terms are calculated in advance and combined with the updated noise source intensity to generate new noise maps.

In [12], the researchers are using traffic sounds (honking) to improve vehicles' traffic noise prediction. They have considered the following road traffic parameters: traffic volume, percentage of heavy vehicles, honking occurrences, and the equivalent continuous sound pressure level. The results they obtained have been compared on the basis of mean square error, correlation coefficient, coefficient of determination, and accuracy. It has been observed that honking is an important parameter and contributes to the overall traffic noise in congested Indian road traffic conditions.

Other researchers are focusing on the vibration in smart traffic. In [13], researchers were using vibration analysis to do real-time road pothole mapping in the smart city. They proposed a reflectometry method to realize real-time pothole observation with vibration signals analysis and spatio-temporal trajectory fusion. They developed prototype devices that measured the acceleration signal mounted on the wheel steering lever and implemented edge signal processing and spatio-temporal information fusion on the prototype for validation. Their results demonstrated that the suggested method was not limited by vehicle type, speed, or engine operating condition. In their road experiment, the proposed method provided stable, efficient, and real-time pothole observation results.

In [22], researchers were analyzing ground vibrations induced by double-line subway trains and road traffic. Because of the specific needs for the research, their field measurement was carried out in Shenzhen, China, where a double-line subway passes directly under the main urban road. Their measurement shows that horizontal acceleration cannot be ignored in the area close to the subway line, and the vibration amplification phenomenon exists in the free field, due to the difference of the local geological conditions that lead to different vibration levels. The measured data can guide the work of vibration environment assessment in the stage of subway design and planning and can also validate possible numerical models for predicting train-induced vibrations.

3. A model for implementing vibration and sound heatmaps in smart cities based on crowdsensing data

The data was collected using the CrowdSense mobile application. CrowdSense application was developed as a part of the research [14][15]. The sensors that were used for collecting noise and vibration data were microphones and accelerometers.

The overall flow chart diagram about the model is shown on the figure below.

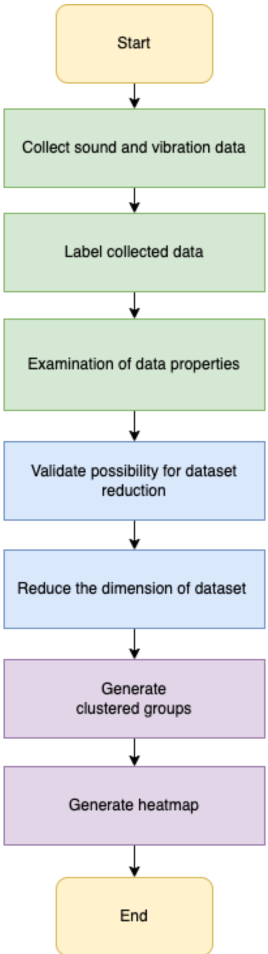

Fig. 1. Proposed model flow chart diagram

Measurements were made at different micro-locations in Novi Sad, by recording 10 to 20 measurements per micro-location per day. Measurements were taken from 1st to 15th April 2021 in four locations. These locations are marked as:

- Location A - Partizanska street
- Location B - Jase Tomica street
- Location C - Bulevar Oslobodjenja
- Location D - Bulevar Evrope

Table 1. Number of measurements per location

Location	Total measures	Measurements from 8:00 to 16:00	Measurements from 16:00 to 00:00
Location A	312	184	128
Location B	268	142	126
Location C	212	127	85
Location D	194	102	92

Source: Data collected as a part of the research

Collected data are labeled using the following labels:

Table 2. Data labels in R language

Name	Data type	Description
Id	Integer	Identification for each measurement
Location	Factor(r) – 4lvl	Locations where measuring took place (4 in total)
AverageValue	Num	Average value in decibels
MaxValue	Num	Maximal value in decibels
Latitude	Num	Distance north or south of the Equator
Longitude	Num	Distance east or west of the prime meridian
MeasurementDate	Date	Date of measurement
MeasurementDay	Factor(r) – 7lvl	Day of the week of measurement
MeasurementTimePeriod	Factor(r) – 2lvl	Period of the day of measurement
Frequency	Num	Value for each frequency, 0 - 100

Source: Author own work

The initial dataset thus obtained had 433 variables and 986 observations. Due to the volume of the dataset and its specificities, as well as for the success of the analysis, it was decided to reduce the dimension of the given set. By manually examining the frequency values, it was found that they decrease as the frequency height increases. It was decided to use the first hundred frequencies for further analysis. The new data set was cleaned of outliers so that all values above the 90th percentile were reduced to their value.

The next step is an examination of the data properties. The analysis was started by determining the dependence of the selected variables. As it is about quantitative variables, Pearson's correlation was applied [16], and the results are presented in the figure below.

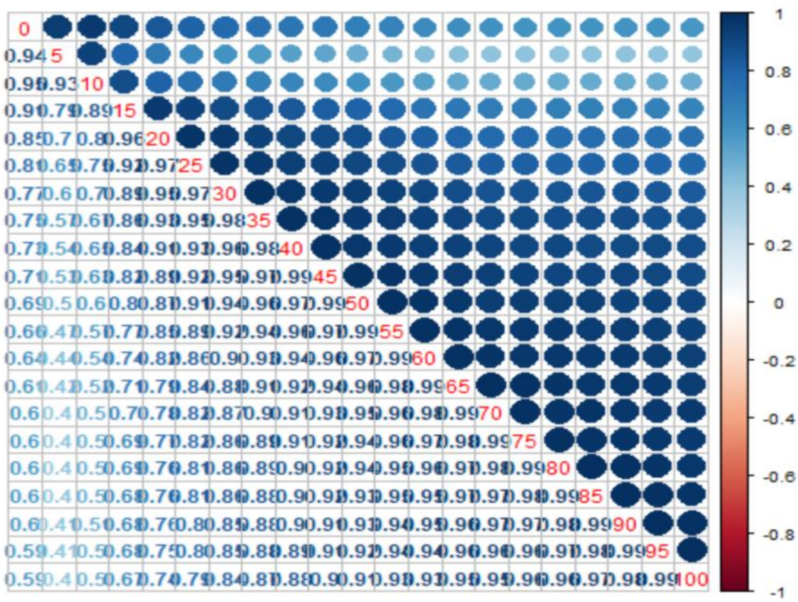

Fig. 2. Pearson's correlation matrix

From the displayed matrix, it is possible to conclude that most frequencies are highly correlated. For example, frequencies 15 and 20 are highly positively correlated ($\rho = 0.96$), while they are slightly less correlated with other frequencies, so it may be beneficial to examine their relationship in more detail.

Based on the obtained results, Principal Components Analysis is applied in order to reduce the dimension of the data set made up of a large number of mutually correlated variables [17].

However, before using Principal Components Analysis, it is required to check if the data is suitable for its use. The results are shown in the following table:

Table 3. KMO and Bartlett's Test

Method	Result
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.913
Bartlett's Test of Sphericity Approx. Chi-Square	271635.270
df	210
Sig.	.000

Source: Author own work

The Kaiser-Meyer-Olkin coefficient (KMO) [18] shows the suitability of applying principal component analysis to the given data and takes a value from the interval [0,1]. A KMO with a value greater than 0.6 is considered adequate. As the KMO in Table 3 is equal to 0.913, the analysis of principal components is considered justified. By Kaiser's criterion [18], it was decided to construct two main components, which cover 93.342% of the total variability.

The next graph shows the result of the "Scree test" [18], which observes the eigenvalues of the corresponding components, and then looks for the largest break in the line that connects it. As in this case the break is at component three, the method suggests two components for further analysis.

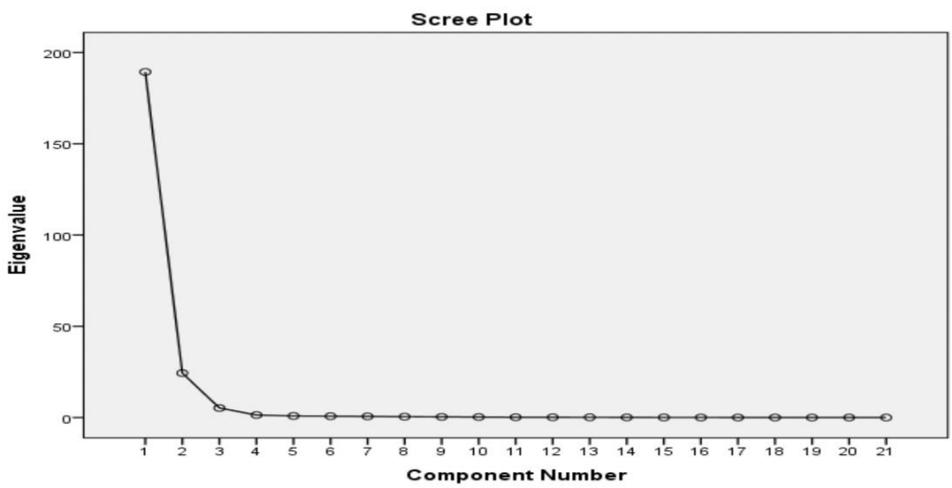

Fig. 3. Scree plot

The results of the principal components analysis method, obtained by orthogonal Varimax [19] rotation is shown on the following figure.

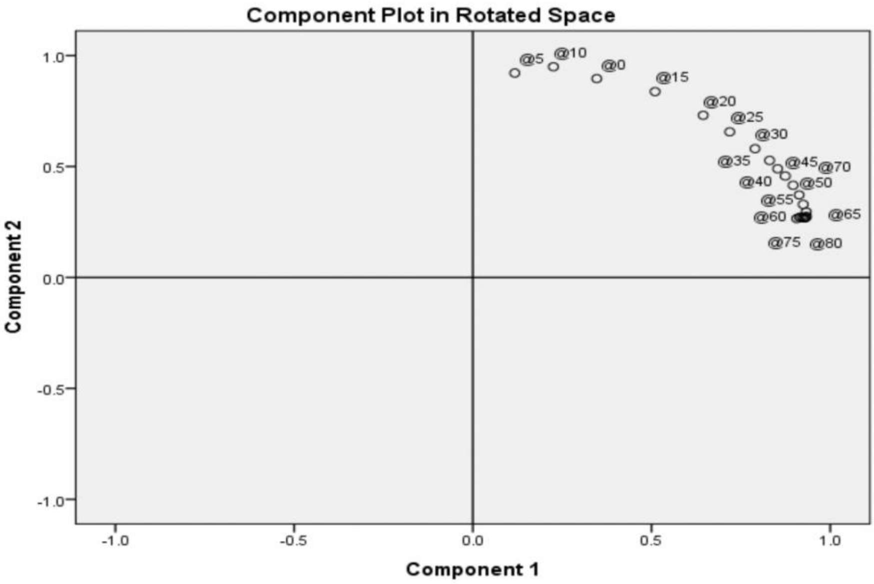

Fig. 4. Principal component analysis results after rotation

As can be concluded from figure 4 - frequencies 0, 5, 10, 15, and 20 belong to one component, while the rest belong to another component. Since it is adequate to use the components constructed in this way, further investigation will be conducted by analyzing the characteristics of the data through these two components.

As a part of the further data analysis, we are performing clustering in order to understand how data could be grouped. For that, we are using the K-means algorithm and the dimension of the original data set was reduced.

The k-means algorithm is an iterative algorithm that tries to partition the dataset into K pre-defined distinct non-overlapping subgroups (clusters) where each data point belongs to only one group. It tries to make the intra-cluster data points as similar as possible while also keeping the clusters as different as possible [19].

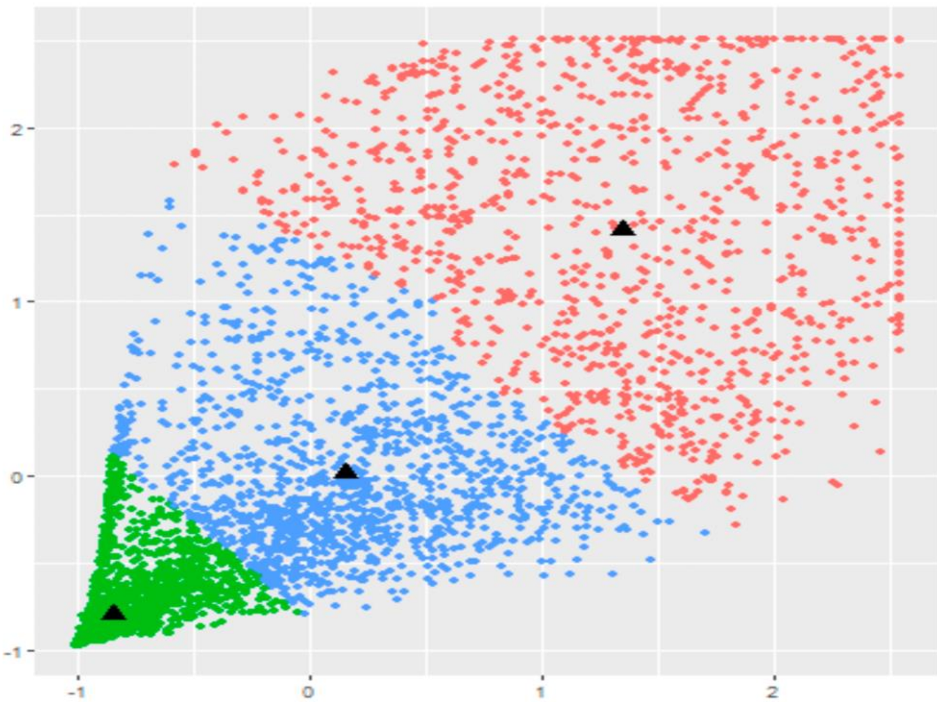

Fig. 5. Measuring depending on the vibrations intensity

Conclusions related to the measuring depending on the intensity of the vibration are:

- 68,99% of measurements from location A belong to group 2 (green), which represents a group with the smallest intensity of vibrations.
- Measurements from location B mostly belong to group 1 (red) and group 3 (blue), which flags this location as significantly louder. But, we also have some measurements that are among the lowest intensity. These kinds of unclear results are coming from the difference in days of the week and different periods of the day.
- Specifically, on location B, Wednesday and Saturday have the highest vibration intensity, so those measurements belong to group 1 (red). Sunday is the day with the lowest intensity of vibrations and those measurements belong to group 2 (blue).
- For locations C and D, there is a similar scenario as for location B, but with even higher intensity. Measurements in location C mostly belong to the group with the highest and lowest intensity of vibrations. Only a few measurements belong to the middle vibrations intensity groups. The reason is the same as for location B.

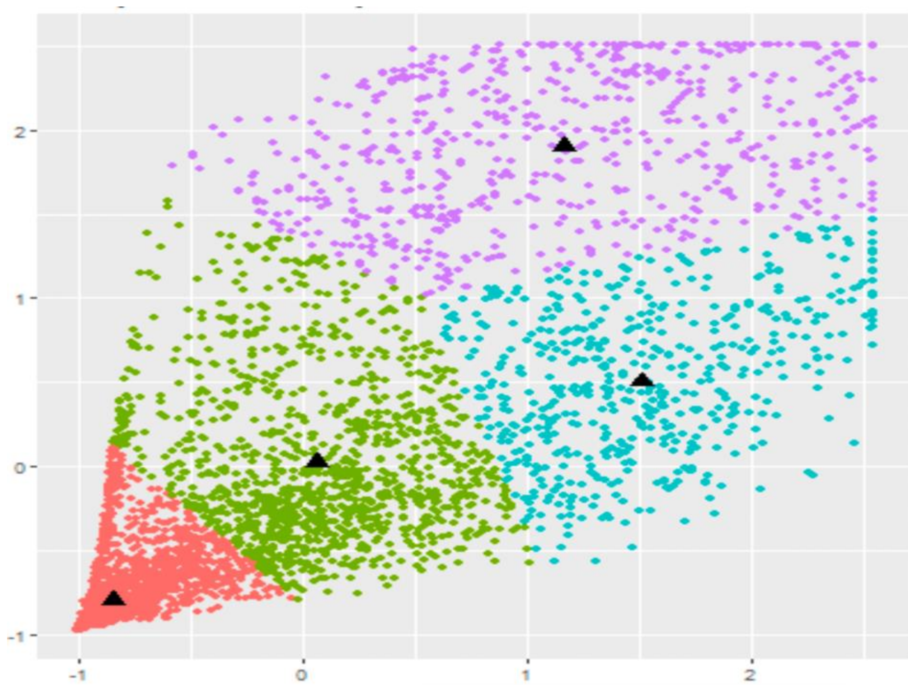

Fig. 6. Measurements depending on the sound intensity

Conclusions related to the measuring depending on the sound intensity are:

- Most of the measurements for location A belong to group 1 (red). That is the group with the lowest noise intensity.
- For location B, around 60% of the measurements belong to group 1 (red) and group 2 (green) with lower noise intensity.
- For location C, most of the records belong to the lowest and highest noise intensity zones. This is related to the working days and time of the day when the measuring was done.
- For location D, most of the records belong to the lower noise level.

The next step is generating heatmaps for sounds and vibrations. The heatmap uses colors on in the map to show the recorded intensity. The collected results are grouped by similarity. As many points we have around a specific location (latitude, longitude), it shows the higher intensity of the color. Google Maps Heatmap API is used to create a noise and vibrations map at targeted locations. The figure below shows heatmaps for all four locations.

Fig. 7. Heatmaps for sounds and vibrations intensity

As we can see in the heatmaps on the figure above, the main separation can be done into three different perceptual attributes:

- Calm - green
- Pleasant - yellow
- Unbearable – red

There are some areas that are marked in some other color, which is a mixture of the two colors. Those areas are on the border between two zones (ex. orange is between yellow and red).

4. Discussion

There are studies that are focused on the analysis of sounds and vibrations in smart cities. Studies are usually considering what kind of pollution excess sound and vibration can do to the human from a medical perspective. It is important to mention that excess sound and vibration can harm the environment in many ways.

Even though awareness of environmental pollution in traffic is growing, there is enough space for improvements in current solutions.

As mentioned in [20], noise pollution has impacted our health in the urban landscapes. Researchers there provide an application that can make noise maps to manage possible noise pollution. Without the application, the data collection requires reliable noise measuring devices installed at different locations for a prolonged period. Their application can generate a noise map at a targeted region at a much lower cost to alert users of a possible increase in the urban area's sound pressure level.

In [21], authors are focused on using a crowdsensing-based platform for transportation infrastructure monitoring and management in smart cities. They define it as an upcoming framework that has the potential to become a high-level monitoring tool and help manage populations of infrastructure systems with reduced cost and increased efficiency in future smart cities. Using that framework, the existing infrastructure system can be prescreened on a large scale to determine the key infrastructure elements that exhibit abnormal behavior before implementing more detailed on-site monitoring systems or conducting detailed site inspections on individual infrastructure elements. In the long term, they envision that their platform will be open-sourced and capable of processing many algorithms and able to support multiple data formats.

The suggested model for implementing vibration and sound heatmaps in smart cities has the main goal to make information on sound and vibration in the traffic more visible and easier to understand to a general audience, which can be a base for decreasing sound and vibration pollution in smart cities, making cities a more comfortable place to live in. We acknowledged that the proposed solution also has some limitations. The main limitation of the proposed model is that it is based only on sound and vibration and it doesn't take into consideration any other source of pollution in the traffic in smart cities.

5. Conclusion

At the time of writing, there are not many considerations on measuring sound and vibration in the traffic of smart cities and how this data can be used for decreasing pollution caused by it.

This can be more important for people that have some hearing disorders, or for special age categories, like elderly people or babies, for which the reduced pollution in sound and vibration can be more valuable. It is important to mention that in the future it might be even necessary to measure this pollution as a part of standard pollution measurement in the traffic environment.

In the future, this research can be used as a base for measuring and tracking the influence of sound and vibration pollution on traffic participants in the cities.

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