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A Study of the Ambient Noise in the Public Space on Campus and the Correlation Between the Campus Crowds' Ambient Noise and the WiFi Log

Yun Jie Lim [a], Seanglidet Yean [a]*, Bu Sung Lee [a], Peter Edwards,[b]

[a] *School of Computer Science and Engineering, Nanyang Technological University, 50 Nanyang Ave, 639798, Singapore*
[b] *Manaaki Whenua – Landcare Research, Box 10345, The Terrace, 6143, Wellington, New Zealand*

Abstract

Urban noise is becoming more serious and increasingly concerning environmental problems. This has led to numerous studies on traffic noise. However, not many studies have been done on noise from a human perspective as they go about their daily life. In another aspect, using of the crowd-sourcing platform is on the rise as the usage of personal devices (smartphones) and the deployment of Internet-of-thing increases. Thus, a large pool of data collected via mobile applications enables users to measure the environmental factor directly and provide immediate feedback for and community's greater good. In this paper, we utilize the crowd-sourcing platform to collect noise data by volunteers to study the noise level in a campus environment, in open common areas which are frequented by students. We are able to map out the noise across the campus from the perspective of the students. The noise level increase through the day as the student gather around popular open spaces. Our study shows that the sound level on campus is due mainly to human and mechanical noise. By combining the noise data with WiFi log data, we were able to show a good correlation between sound level and human density in an area.

Keywords: *sound level, ambient noise, environmental noise monitoring, environmental noise analysis, urban noise*

1. Introduction

Noise/sound levels in urban areas is increasing around the world due to increased industrial, human activity and human density in the urban environment. Noise is addressed in two relevant World Health Organization publications. [1] looks at noise assessment, meanings, effects, occupational exposure and injury, and damage-risk parameters, while [2] considers noise in the light of other housing environmental factors. Addressing the challenges emerged with the urbanization of smart cities, there are research interest in smart pollution measuring and controlling, particularly making use of the cloud-based, crowd-sourced and available data [3].

Initial studies on noise have been focused on major noise sources, such as Traffic, airplane noise and industrial noise. [4] discussed about the differences in people's annoyance towards high frequency components found in road traffic noise and low frequency components found in Jet aircraft noise. Sonaviya and Tandel [5] developed a correlation factor between road traffic noise and heterogeneous traffic conditions in an urban Indian context. Ueda, Tanaka, Nakamura and Miura [6] attempts to measure the degree of understanding of the size of the sound felt by university students through their proposed loudness chart kit. However, the measurement was severely limited by the lack of knowledge of other sound noises by students. As smartphone technologies advance, it holds a huge potential in enabling data fusion as well as patterns and trends analysis for well-being with its sensors and

*Corresponding author. Tel.:
Fax: ; E-mail: seanglid002@e.ntu.edu.sg
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connectivity [7]. Hence, ambient sound analysis could be taken a step further with the combination of sensor data, mobility pattern and user perception.

Our studies will focus on the noise level students encounter in open areas on campus. Students spend much of their time on campus in lectures and in open areas. Our initial study showed that on top of the lectures, the campus is a social melting pot, where students interact with each other in open areas [8]. The study is based at the Nanyang Technological University (NTU) campus [9] which has a student population of over 33,000 students and spanning an area of 200 hectares. The main open area of common activity on campus is on the North and South spine. Stretching out from the main spines are the different schools, e.g. School of Computer Science and Engineering (SCSE).

In this paper, we conduct experiment based on the research questions below:

- How loud is the sound level around campus?
- How does the campus crowd dictate the noise of the area?
- What are the contributing factors to the campus ambient noise?

2. Data Acquisition and Pre-Processing

In order to study the noise level with regards to campus's crowd, two data sources are used: the noise level data crowd sourcing by volunteers and the campus Wi-Fi log records.

2.1. Noise Measurement Parameters

Understanding the ambient noise in the environment requires the noise measurement aspects such as sound pressure level, sound intensity level, and frequency. While sound intensity indicates a vector of flow of sound power through a specific area per unit of area, sound pressure is the scalar quantity perceiving sound energy from sound sources at a specific location in an acoustical environment. The key to accessing noise pollution is sound pressure level as it measures amplitude level of sound energy from sound sources at a specific location. In particular, Sound level $LAeq$ provides average sound "pressure" over a given period for constant or continuous noise. $LAeq$ refers to the A-weighted filter being used to calibrate the Leq sound level [10]. A-weighting is the standard frequency-weighting for sound level meters, covering the full audio range, 20Hz to 20kHz and it tries to mimic the human response to sound levels. The sound level is measured in units of decibels (dB).

In this study, we focus on a noise exposures: Sound Level LA_{eq} (Eq. (1)), and Sound Spectrum (Frequency).

$$LAeq = 10\log_{10}\frac{1}{T_M}\int_0^{T_M}\left(\frac{P_A(t))}{P_0}\right)^2 dt \qquad (1)$$

where P_0 is the reference sound pressure of $20\mu Pa$ of 1 dB and $PA(t)$ is the instantaneous A-weighted sound pressure (PA) of the sound signal.

Table 1. Attribute of noise data.

Attribute	Description
Time Datetime	the time of recording
Time Epoch	the time in unix form
Noise Level	the sound level in LAeq in db(A) 1s
Leq_frequency	the sound level at different frequency band (Hz)
Speed	the speed of the estimated device in m/s
Geometry	the coordinates of the point in latitude and longitude

2.2. Noise Data Collection

In the real world, sounds are generated from multiple sources.

In an urban environment we are bombarded by sound from human and machines. The sound level is aggravated by greater urbanisation, human density and the concrete jungle we built.

With the advent of smartphone with better sensors, we can use smartphones to measure various data from the perspective of the human [11]. Thus, in this case, we are focusing on the sound level that humans encounter as they move about in their daily life.

In our project, we are using smartphone as the sound sensor. The sound dataset was collected using an Android application called NoiseCapture [12]. NoiseCapture measures the sound along the path. The data is share with the community through various online platforms such as data.noise-planet.org.

The sound measurements collected from smartphones are organized in 3 zipped GeoJSON files: tracks.geojson, points.geojson and areas.geojson, based on coordinate reference system with EPSG 4326. The points.geojson was used as it provides the coordinates of every sound point measured and hence most applicable to our study.

Table 1 lists the attributes used in the analysis. The collected data is sampled and processed every 1 second. As a result, we have the recording of time of recording, average sound level, sound level at different frequency band, collector's moving speed and coordinate per second.

The data collected using NoiseCapture application are uploaded to the community [13]. It is to be noted that the data uploaded exclude the sound spectrum. Thus, for a detailed analysis, we made use of the local data collected using NoiseCapture application, which includes the sound spectrum. The data were collected over 2 weeks from 22nd January 2021 to 5th February 2021. Using the application, volunteers start recording during their free time as they walk around campus (e.g. going from class to class, walking leisurely around campus, or going for a meal). While doing the recording, volunteers keep quiet to record the surrounding sound. Each recording was of a few minutes and it was exported to the local PC for analysis.

2.3. Wi-Fi Data

In our previous study on student mobility, we were able to capture the approximate location and mobility pattern of students using the anonymised Wi-Fi log data [14]. With

Table 2. Attribute of the anonymised Wi-Fi log data.

Attribute	Description
Mobile device MAC address	the unique identifier assigned to a network interface console.
Start of connection	data and time stamp of the exact start date-time that user connects into the network.
Duration of connection	the duration of session at which user connects to the network with a device (Disassociation Time – Association Time)
AP id	the unique identifier for each AP

Table 3. Attribute of the derived information from Wi-Fi log data.

Attribute	Description
AP general location	Derived from the AP Name stating the general location of the AP (E.g. N2.1, NS3, NS4, etc.) This attribute is also known as the block name.
Connection End	The time stamp of the exact end date-time that user disconnects from the network/
Floor	Floor number where the Wi-Fi access point is placed.

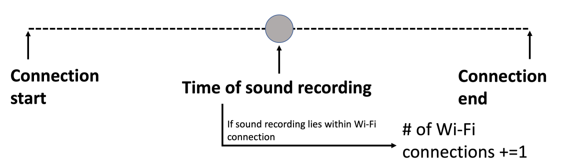


Fig. 1. Estimate WIFI_CONNECTIONS at the time of sound recording

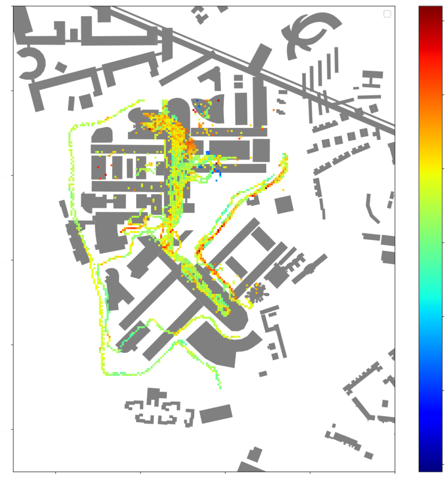


Fig. 2. 95th Percentile of Sound Level (dB(A))

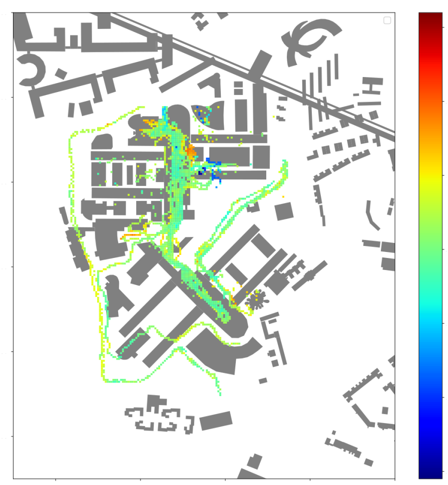


Fig. 3. Minimum of Sound Level (dB(A))

attribute described in Table 2, additional information are extracted such as the general location of the access point and floor number from AP id as well as end of connection from start of connection and duration of connection (Table 3). Hence, it is possible to determine the time a specific mobile device is located.

Therefore, in order to determine the crowd size at the time and location of the sound recording, the number of Wi-Fi connections ($wifi\_connections$) is derived as depicted in Fig. 1. It means, at the sound recording timestamp, $wifi\_connections$ is counted if $wifi\_connections$ is connected to the access point situated within the same block (5m x 5m) of the sound recording's geometry.

3. Data Analysis Experiments

3.1. Analysis of Sound Around Campus

The first experiment was carried out to profile the sound level along path frequented by students. Fig. 2 and 3, mapped by algorithm Fig. 5 representing the noise recorded in the assigned grid, show the sound map of the main campus area. The grey colour are the buildings located in the university compound. The variation of colours represents the sound level: the further red in the rainbow spectrum, the higher the sound level. Each square block area has the resolution of 5 x 5 meter square. The sound data was recorded after the start of the university semester,

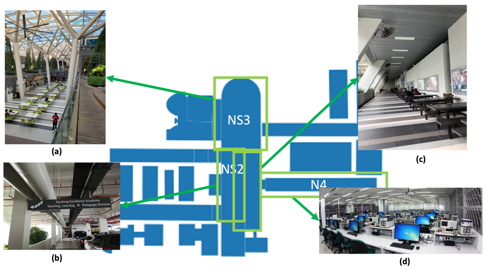


Fig. 4. Point of Interest
(A) Block NS3, (B) Walkway at Block NS2, (C) Walkway at Block NS4 and (D) Laboratory in Block N4

starting from 11th January 2021, was used to ensure the correct representation of the student population density.

Significant differences of sound level between the minimum sound level (baseline ambient noise) and the 95th percentile of sound level could be observed. For instance, the orange/red spots are concentrated at the top end which is where Block NS3 is located (the illustration of the point of interest is shown in Fig. 4). This is expected as students gather there for lunch. For the areas with similarity in sound level between the 95th percentile and minimum sound levels, it depicts sparse crowd and low in pedestrian traffic, in contrast to the high variation seen at NS3.

Answering *How loud is the sound level around campus?*, the differences of sound level could be observed in Fig. 2 and 3. Additionally, we could identify the area of interest (NS2, NS3 and NS4 in Fig. 4) to analyse the average sound level and campus crowd.

3.2. Analysis of Sound level and Crowd Estimation at Point of Interests

To further dive into the correlation between human activity and sound level, we looked at the correlation between the number of Wi-Fi connections and sound level. Pearson product-moment correlation coefficient (PPMC), or the bivariate correlation [15], is used to measure of linear correlation between the mentioned two sets of data.

Table 4. Correlation between Wi-Fi connections and Sound Level

Point of Interest (PoI)	PPMC	Collectors' Traveling Speed (m/s)	PoI Description
NS3	0.379	0.51109	common gathering area
NS2	0.495	1.08009	walk way to NS3
NS4	0.598	1.14237	walk way to NS3
N4	-0.048	0.56335	laboratory

The PPMC between the number of Wi-Fi connections and the number of sound level is shown in Table 4. It is assumed that each student on average represents 1 Wi-Fi connection. Overall, the blocks, NS2, NS3 and NS4 show positive correlation. It means the higher sound level is corresponding to the higher crowd density. A possible reason why NS3 has a lower correlation compared to the two other blocks might be because it is located at the north spine plaza. The north spine plaza is the dining area filled with many food and beverage outlets as well as many tables and chairs for dining. This means that there is higher likelihood that people are talking louder than usual. Furthermore, the collectors' average speed for NS3 is significantly lower than blocks NS2 and NS4. This further validates the hypothesis that the sound recordings are taken when the volunteers are dining or standing still. A reason why the average speed of N4 is also low could be because N4 is the academic block for computer science students filled with laboratories and tutorial rooms, not at the open space. Therefore, similar to NS3, most of the recorded data are of students doing their lab work, with minimal mobility.

This experiment addresses *How does the campus crowd dictate the noise of the area?*. A good correlation was found between the higher crowd density and sound level when the areas of interest are in open and public space. There could be exception affected by zoning or special circumstances of the area that restrict making sound such as the public space next to the enclosed student-filled area (e.g. laboratories and libraries) that the Wi-Fi connection does not correlate with the crowd sound.

3.3. Analysis of Sound Source - human sound and other potential sound sources

This experiment's objective is to identify the sources of the sound and the differences in the sources as the number of Wi-Fi connections increase. The sound spectrum ranges' reference for various sound sources of sound is reported in [16].

In this study, we focus on the point of interest (PoI) at NS2, NS3, and NS4 with a total of 7924 sample Wi-Fi connections data. Fig. 6 shows the distribution of the number of Wi-Fi connections. It is seen that the number of Wi-Fi connections is heavily left-skewed and Wi-Fi connections that are more than 210 are identified as outliers. For analysis, we will look into two group of data:

- Group A: contains 13 or less Wi-Fi connections (25th percentile)
- Group B: contains 97 or more Wi-Fi connections (75th percentile)

We have plotted correlation matrices for group A and group B between the sound level (L_{eq}_mean) and sound spectrum (Fig. 7 and 8). This section aims to visualise the correlations more clearly by plotting and comparing the graphs of highly correlated and lowly correlated frequencies.

In addition, Fig. 9 shows the average sound level (defined as leq_mean) as well as sound level generated at 500Hz (defined as leq_500) and 1600Hz (defined as leq_1600) for group A. As observed, leq_500 has a high correlation coefficient of 0.853 with the sound level and leq_16000 has a low correlation coefficient of -0.05 with the sound level. This is also evident in Fig. 9 as the pattern of the line plot of leq_500 follows closely to that of leq_mean whereas the pattern of the line plot of leq_16000 differs greatly from leq_mean.

Algorithm: Noise Mapping from Raw Noise Data to Visualisation Map

procedure *NoiseSquare*
$x \leftarrow$ longitude of top left grid (starting point)
$y \leftarrow$ latitude of top left grid (starting point)
$x_{iter} \leftarrow$ number of iterations horizontally
$y_{iter} \leftarrow$ number of iterations vertically
$x_{inc} \leftarrow 0.000085$ #static increment
$y_{inc} \leftarrow 0.000085$ #static increment
$i \leftarrow 0.$
$x_{left} \leftarrow x$
$x_{right} \leftarrow x + x_{inc}$
$y_{top} \leftarrow y$
$y_{bottom} \leftarrow y - y_{inc}$
data $\leftarrow$ []
while i < y_{iter} **do**
coords $\leftarrow [(x_{left}, y_{bottom}), (x_{right}, y_{bottom}), (x_{right}, y_{top}), (x_{left}, y_{top})]$
poly $\leftarrow$ convert *coords* to polygon shape file
point_square $\leftarrow$ all noise point in the *coords*
if *point_square* > 0 **then**
min $\leftarrow$ minimum noise level of point_square data
max $\leftarrow$ maximum noise level of point_square data
append ***data*** list with (*min, max, poly*)
j $\leftarrow$ 0
while j < x_{iter} **do**
$x_{left} \leftarrow x_{right}$
$x_{right} \leftarrow x + x_{inc}$
coords $\leftarrow$
$[(x_{left}, y_{bottom}), (x_{right}, y_{bottom}), (x_{right}, y_{top}), (x_{left}, y_{top})]$
poly $\leftarrow$ convert *coords* to polygon shape file
point_square $\leftarrow$ all noise point in the *cords*
if *point_square* > 0 **then**
min $\leftarrow$ minimum noise level of point_square data
max $\leftarrow$ maximum noise level of point_square data
append ***data*** list with (*min, max, poly*)
j $\leftarrow j + 1$
i $\leftarrow i + 1$
$x_{left} \leftarrow x$
$x_{right} \leftarrow x + x_{inc}$
$y_{top} \leftarrow y$
$y_{bottom} \leftarrow y - y_{inc}$

Fig. 5. Noise Mapping Algorithm

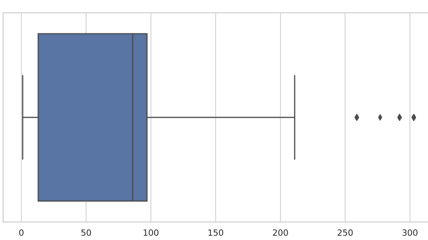


Fig. 6. Number of Wi-Fi Connections

Group B also displays similar observations. Fig. 10 shows the average sound level as well as sound level generated at 125Hz and 1250Hz for group B. leq_125 has a low correlation coefficient of 0.33 and leq_1250 has a high correlation of 0.866 with leq_mean. Fig. 10 shows the pattern of the line plot of leq_1250 following closely to that of leq_mean and the pattern of leq_mean differing greatly to leq_125.

There is a difference in the distribution of correlation between average sound level (leq_mean) and sound level at different frequencies. In group A, there is a high correlation (> 0.74) between mean sound level and sound level of frequencies between 250Hz and 1250Hz whereas, in group B, there is a higher correlation between average sound level and sound level of frequencies between 630Hz and 2500Hz. We can observe that the background sound from generators, airflow, which has low frequencies between 8 to 500Hz according to [16], contributed greater to the sound level for group A compared to group B. On the other hand, speech tends to be a greater contributor to background sound for group B compared to group A.

This observation could be reasoned with the positive correlation between the number of Wi-Fi connections and the presence of people. Sound data in group A has much lesser Wi-Fi connections than group B and this means that there is likely to be fewer people. With low number of

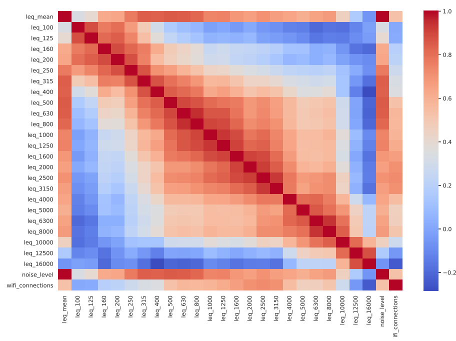


Fig. 7. Correlation Matrix for Group A

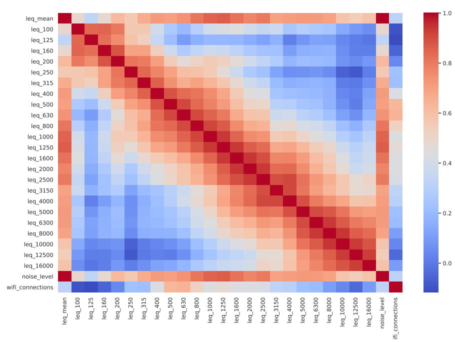


Fig. 8. Correlation Matrix for Group B

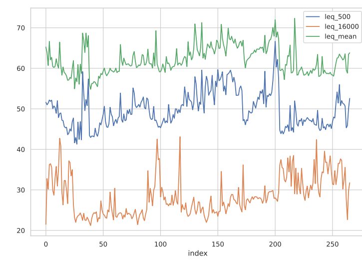


Fig. 9. Leq500, Leq1600 of Sound Level of Group A

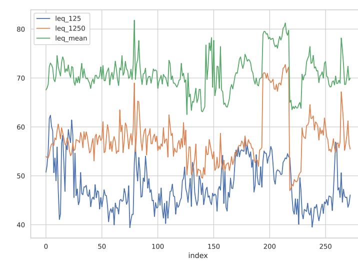


Fig. 10. Leq120, Leq1250 of Sound Level of Group B

people, the major source of sound in group A is from the sound from generators, airflow, etc. Likewise, with more people, the major source of the sound in the data for group B is from human.

3.3.1. Case Study on Selected Noise Recording

The case study (Fig. 11) is conducted using selected noise recording samples, R_309320 and R_311816. It is to further explain explain the key differences in the area of different crowd, where R_309320 consists of a lower average noise level and number of Wi-Fi connections than R_311816.

It was observed that there are significant differences in the distribution of correlation coefficient between the mean noise level and the noise level of specific frequencies. The correlation matrix of R_309320 has a high correlation for frequencies between 100Hz and 1600Hz whereas recording R_309320 has a high correlation for frequencies between 630Hz and 4000Hz. As the background noise common in the setting of a university such as from ventilation and generators have a low frequency and the frequency of human speech is between 500Hz and 3500Hz. Therefore, the origin of noise for R_309320 is most likely from background noise and human speech is most likely the source of noise generated in recording R_311816. In addition, a positive correlation between the number of Wi-Fi connections and the average noise level could be observed.

The comparison further illustrate the differences in the distribution of correlation coefficient between R_309320 and R_311816 more clearly. According to the sound spectrum, the line plot of the lower frequencies follows closely to that of the average noise level whereas, while the line plot of the higher frequencies follows closely to that of the average noise level. Thus, this verifies the main noise sources for the two different recordings. R_309320, where there is a high correlation between average noise level and noise level at lower frequencies, has its major source of noise derived from background noise such as generators and airflow. On the other hand, R_311816, where there is a higher correlation of average noise level and noise level at higher frequencies, has its major source of noise derived from human speech.

Through these case studies, the answer to *What are the contributing factors to the campus ambient noise?* could be addressed on circumstantial basis. During the data collection period of this study (Jan-Feb 2021), the higher sound level relates to the human crowd in the area while lower sound level depicts machinery sound from generators, air-flows, etc. It could be circumstantial as the background sound reflects the renovation the university initiated during the reporting period at the area of interest.

4. Conclusion

In this study, we have observed the minimum and maximum sound level recorded per unit area across the campus, where there is a large variation in maximum sound level across the campus with high sound levels concentrating at NS3, one of NTU's key student hubs. There is a gradual change in sound level over time, peaking at lunch and end of work hours which are peak traffic hours and toughs at low-peak

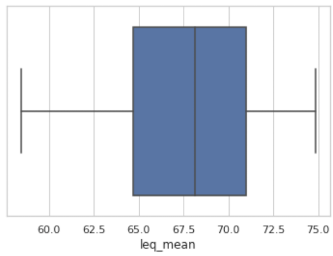
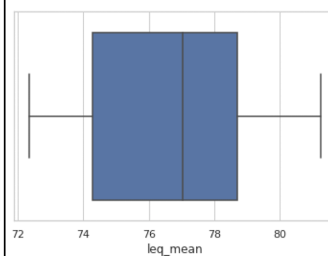
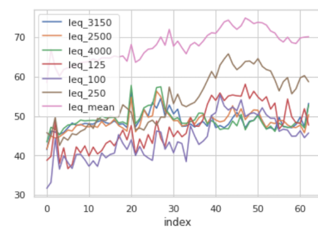
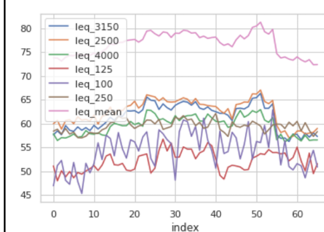
	R_309320	R_311816
Average Noise Level	68	77
Number of WiFi connection	12	73
Noise Level		
Sound Type (Sound Spectrum)		

Fig. 11. Comparison Summary - Sample 309320 and 311816

hours in mid-afternoon. By combining sound data with Wi-Fi log data, we are able to show the good correlation between sound level and human density in the open and public area while there are exceptions; in particular, the corridor next to the student-filled laboratories. By inspecting the signal strength at various frequency bands, we were able to differentiate the sound due to human and verify that the correlation is indeed correct. The analysis reflects the university's circumstances having a more spread-out crowds in effect of the COVID-19 activities restriction and renovation observed in sound sources of the background noise.

The limitations of the study could be the fact that correlation insight must take into account the exception cases by removing the neighboring sub-zone which yeilds Wi-Fi connections that does not correspond to the area of interest or excluding the noise-restricted area. For the sound source analysis, it was done based on the correlation analysis and observation. To improve on the study methodology, a prediction model could be used to quantify the dominant sound at the area of interest with the sound spectrum as the input features. Lastly, obtaining the data could be a challenge where privacy and availability are concerned. However, we are using NoiseCapture application to collect data and mitigate the issues where the crowd audio was not stored, instead the pre-processed sound spectrum was saved. The WiFi data was anonymised and left with the available attributes.

In future work, further studies and recommendation on crowd control could be done using Wi-Fi log data to lower the average sound level, potentially to formulate or evaluate the organisation policy or regulation. In addition, We will be carrying out investigation into sound and the vegetation coverage across Singapore and in the town of Wellington, New Zealand. The relationship between vegetation and sound is only one part of the project work package on trees and human beings.

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