KNOWLEDGE DISCOVERY OF NOISE LEVEL IN LECTURE ROOMS

By:

TANG JAU HOONG

(Matrix no.: 125051)

Supervisor:

Dr. Loh Wei Ping

May 2018

This dissertation is submitted to

Universiti Sains Malaysia

As partial fulfilment of the requirement to graduate with honours degree in

BACHELOR OF ENGINEERING (MECHANICAL ENGINEERING)

School of Mechanical Engineering

Engineering Campus

Universiti Sains Malaysia

Declaration

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed: ____________________
(TANG JAU HOONG)

Date: ____________________

Statement 1

This thesis is the result of my own investigation, except where otherwise stated. Other sources are acknowledged by giving explicit references. Bibliography/references are appended.

Signed: ____________________
(TANG JAU HOONG)

Date: ____________________

Statement 2

I hereby give consent for my thesis, if accepted, to be available for photocopying and for interlibrary loan, and for the title and summary to be made available outside organizations.

Signed: ____________________
(TANG JAU HOONG)

Date: ____________________

Acknowledgement

Firstly, I would like to express my deepest gratitude towards my supervisor, Dr. Loh Wei Ping for her effort, her patience and her time in supervising, assisting and guiding me throughout the entire project. She had shared much invaluable knowledge regarding the project which had improved and help me a lot in conducting the project. I am sure her input will be very valuable to prepare me towards a future successful engineer.

I would also like to grab this opportunity to express my gratitude towards all my fellow friends, master students, and seniors who often assisted me and offered their help whenever I needed. Without their assistance, I will not be able to accomplish this project in time.

Finally, I definitely feel thankful to my parents for providing the moral support and advice all the time. Without them, I would not be where I am today.

It is always impossible to personally thank everyone who has facilitated and helped me for successful completion of this project. To those whom I did not mentioned specifically, I would also like to acknowledge my gratefulness for assisting me towards accomplishing my goal.

Table of content

List of figures

List of tables

Nomenclature

DK	Dewan Kuliah, Lecture Room
MEK	Mechanical Lecture Room
WEKA	Waikato Environment for Knowledge Analysis
STI	Speech transmission index
MNV	Maximum Noise Volume
BN	Background Noise
RT	Reverberation Time
C50	Clarity 50

Abstrak

Akustik kelas merupakan aspek penting dalam pengajaran dan pembelajaran di peringkat universiti untuk memastikan pelajar dapat menerima maklumat dan pengetahuan daripada pensyarah. Kerja-kerja terdahulu telah melaporkan mengenai penyelidikan akustik bilik dengan menggunakan parameter seperti masa gema, bunyi latar belakang, kejelasan 50 dan indeks penghantaran suara dalam pengukuran. Walau bagaimanapun, ia telah menyedari bahawa tiada usaha dilakukan di ruang syarik fizikal seperti saiz bilik, geometri dan bentuk, dan spektrum frekuensi oleh perlombongan data. Oleh itu, kajian ini menganggap kesan bilik kuliah yang berbeza mempengaruhi tahap bunyi bising. Objektif projek ini adalah untuk membezakan tahap bunyi bising audio dan latar belakang yang bermaklumat dari pelbagai bilik kuliah yang berbeza, untuk mengklasifikasikan tahap bunyi dari langkah-langkah kuantitatif audio dan ciri bilik kuliah dan untuk mengenal pasti corak tahap hingar yang bersesuaian dengan sifat fizikal bilik dan atribut kuantitatif audio. Data audio dikumpulkan dari tiga jenis bilik kuliah yang terdapat di Kampus Kejuruteraan, Universiti. Rakaman audio eksperimen akan berlaku menggunakan 4 telefon yang sama dan pendirian tripod kamera semasa waktu kuliah. Data audio yang dirakam akan melalui pra-pemprosesan data untuk penyaringan nilai luar dan melampau. Klasifikasi data dijalankan dalam dua fasa; pada awalnya pada 23 algoritma pengelas terbina dalam diikuti dengan penyempurnaan tujuh pengelas yang dilakukan dengan lebih baik dengan penyiasatan sifat terpilih menggunakan alat Weka. Analisis corak dan visualisasi akan digunakan pada data untuk mengenal pasti korelasi antara bilik kuliah fizikal dan ukuran kuantitatif audio. Hasil kajian menunjukkan ketepatan 99.5918% dicerminkan pada 6 klasif iaitu J48, Pokok REP, Jadual Keputusan, JRip, OneR dan BAHAGIAN. Penemuan menunjukkan bahawa saiz bilik yang lebih besar, yang lebih rendah akan menjadi STI. Sementara itu, lebih kecil bilik, semakin tinggi bunyi yang dihasilkan secara khusus 10 minit pertama dan 10 minit terakhir syarahan.

Abstract

The classroom acoustics is an important aspect of the lecturing and learning condition in university level to ensure the student able to receive the information and knowledge from the lecturer. Earlier works have reported on the room acoustic research by using the parameters like reverberation time, background noise, clarity 50 and sound transmission index in the measurement. However, it was realized that no efforts were done on the lecture room physical attributes like the room sizes, geometry and shape, and frequency spectrum by data mining. Therefore, this study considers different lecture room sizes impact on the noise level. The objectives of this project are to differentiate the informative audio and background noise level from different lecture room sizes, to classify the noise level from audio quantitative measures and lecture room features and to identify the patterns of noise levels corresponding to the room physical attributes and the audio quantitative attributes. The audio data was collected from three different the lecture room sizes available at Engineering Campus, Universiti. The experimental audio recording will take place using 4 identical phones and camera tripod stand during lecture hours. Recorded audio data will go through data pre-processing for outlier and extreme value screening. Data classification was conducted in two phases; initially on 23 built-in classifier algorithms followed by a refinement of seven better-performed classifiers with selective attributes investigation using Weka tool. The pattern analysis and visualization will be applied to the data to identify the correlation between physical lecture room and audio quantitative measures. The study results showed 99.5918 % accuracy reflected on 6classifers which is the J48, REP Tree, Decision Table, JRip, OneR and PART. Findings show that the larger the room size, the lower will be the STI. Meanwhile, the smaller the room, the higher the noise produced specifically the first 10 minutes and the last 10 minutes of the lecture.

Chapter One: Introduction

1.1 Project background

Classroom acoustics relates to the study on the performance of learners that relate to the sound heard when the message is delivered by the teacher [1]. Whenever the message heard is unclear (in a noisy environment), it will affect the academic performance of the learners. The word sound is often used to describe two different things: an auditory sensation in the ear, and the disturbance in a medium that can cause this sensation [1]. In other words, acoustics deals with the production, control, transmission, reception, and effects of audio in a different medium and different frequency range [1].

Recently, the classroom acoustic has captured the attention of many researchers like Dongre and Patil, Sala and Rantala and Pääkkönen et al. [2] [3] [4]. In Pinho et al., Dongre and Patil, Sala and Rantala and Pääkkönen et al. reported on the methods and approaches to collect audio data from the classroom and the way to digitalize the raw audio data [2] [3] [4] [20]. The raw data were commonly converted into acoustics parameters like reverberation time, clarity, and background noise and speech transmission index. In Gramez and Boubenider, the structure of the building was considered to retrieve more detailed analysis on the classroom acoustics [5].

Although successful studies had reported the classroom acoustic considering different parameters such as the reverberation time, clarity, background noise and speech transmission index, the data mining approach was not adopted. Ideally, data mining approach enables the classroom audio data being categorized into certain and uncertain signals with further detailed analysis performed at knowledge discovery level.

Therefore, this study attempts to discover new knowledge from the audio data with different acoustic and room physical parameters by data mining method. The purposes are to differentiate the informative audio and background noise level from different lecture room sizes, to classify the noise level from audio quantitative measures and lecture room features and to identify the patterns of noise levels corresponding to the room physical attributes and the audio quantitative attributes. Case study data involved an experimental recorded audio from three sizes lecture rooms available at Engineering Campus, University Sains Malaysia. Four microphones will be set up at the different positions in the room to record the audio from the source (lecturer's voice) during the lecture. Data mining approach will be conducted for data analyses under three stages: pre-processing, processing and the knowledge discovery aided by the WEKA tool. The measured attributes include the number of seats, the number of occupants, the rooms' sizes and dimensions, the rooms' geometry and shape, the number and position of the electronic speakers, the student cohort level, gender and age of the lecturer, characteristic of the rooms. The quantitative audio measures include reverberation time, background noise, clarity 50, definition 50, speech transmission index will be calculated according to the data generated from the audio. At data pre-processing process, qualitative data inspections were performed where the outliers and extreme values will be eliminated. Next, the data will undergo two phases of data classification analyses by noise levels based on the amplitude of the noise measured in the maximum noise volume with classifier algorithms. Pattern analysis was observed on the visualization between the attributes to each other.

1.2 Problem statement

Many existing studies on learning environment audio analyses have considered the surrounding atmosphere, the ventilation and lighting of the classroom, time management for each course and the methods of teaching and learning for all educational levels (primary to university). Apparently, sound acoustic parameters like background noise, reverberation time, clarity 50, definition 50, sound transmission index was mainly important had been focused on previous studies. However, the lacking was that no works had reported the significance of the attributing factors to distinguish noise levels. The abundance of data was extracted and collected from classroom audio, but these data remain with little information without efforts to turn them into fruitful data. Data mining approach essentially… Nevertheless, no works have applied data mining in the room acoustic analysis using the room physical attributes like room sizes, room geometry and shape, number of occupants and number of seats as the research parameters.

1.3 Objectives

The purposes of this research project are to:

a) differentiate the informative audio and background noise level from different lecture room sizes.
b) classify the noise level from audio quantitative measures and lecture room features.
c) identify the patterns of noise levels corresponding to the room physical attributes and the audio quantitative attributes.

1.4 Scope of work

Classroom acoustic audio will be collected throughout audio recording during lecture hours at three identified lecture room sizes (DK 1 as large size, DK 8 as medium size, MEK 1 as small size). The rooms were designed on different geometry shapes like stepped profile with fan shape and plain profile with a rectangular shape as layout maps shown in Appendices 1-4. The audio will be recorded using 4 identical iPhone 6 with built-in low-frequency roll off the microphone. The recordings will be digitalized through Audacity Software (version 2.2.1). Based on the frequency, attributes like reverberation time (RT), clarity (C50), definition (D50), speech intelligibility index(SII), speech transmission index (STI) can be tapped.

These data will undergo three stages of data mining analysis aided by Weka software. Pre-processing techniques include the interquartile range filter which can be used to eliminate the extreme value and outliers and randomize filter which can use to mixed up the data set randomly so when the cross-validation applied the data set will not majorly participate by the first experimental data only. Three stage of classification will be applied to the data which is 23 classifiers used to try their performance and the one with better performance will be picked out for the secondary classification. In the second stage, the attributes will be removed one by one to the effects of each attribute will be determined. The third stage will use the visualisation and pattern analysis on the data. The data will be classified by three defined levels of noise (<-10dB as silence, -10dB<x<-5dB as average, and >-5dB as noisy) using 7 classifiers built-in Weka tool.

Chapter Two: Literature Review

2.1 Learning conditions and room acoustic

A quality study is a key predictor for the students' grade [6] and it can be enhanced by using particular study strategies and picking the appropriate physical study environments [7]. Good acoustic for the study environment can give positive effect to the student learning and achievement [24]. Therefore, the acoustic comfort plays a primary role for students learning the ability. To achieve a learning environment with good acoustic, the noises from external like the traffic, from internal like the HVAC systems or chatting need to be minimized [8]. In the Connolly et al. [9] studies, an online questionnaire survey was developed to investigate the elements that determine the perception of the acoustic environment for the high schools [25]. The results of the questionnaire show that the students experience frequent changes of location, subject studied and high levels of noise exposure will cause their grades dropped [9].

The sound has complex effects on learning, and at least five factors underlie this complexity [10]. First, the physical attributes of the sound, such as the decibel level, frequency, and reverberation, have been considered [26]. Noise index is a parameter used to measure a noise in a way which allows people to make some judgment about the noise. The noise index that most widely used in the European countries is the sound transmission index (STI). STI can be calculated from the reverberation time (RT) and signal-to-noise ratio (L¬SN) of an enclosed space [11]. From the previous research, the use of either measured or predicted values of STI provided similar RT and L¬SN with only 0.01 differences in the reverberant room and 0.03 in the absorbent room. Other parameters like A-weighting decibels scale also been used to measure the sound pressure level for an enclosed room. World Health Organization (WHO) has recommended the A-weighting decibels values LAeq,30min averaged 70.5 dB(A) in occupied classrooms, and 38.6 dB(A) in unoccupied ones [12]. The indoor and outdoor noise measurements are suggested that the noise from the outside like the road or laboratory will directly affect the background noise strength in the lecture room but in varying degrees [13].

2.2 Acoustic parameter measurement

There is some standard method used to measure the acoustic parameters like the sound transmission index, reverberation time, background noise and clarity 50.

Speech Transmission Index (STI) is the significantly better with the single octave band and broadband reverberation times where the measurements were taken according to the international standard IEC 60628-16 [14]. A B&K type 4128 HaTs is placed at the lecturer's desk and the measurement using sound level meter is placed in the central position inside the classroom.

Reverberation time (RT), one of the most popular room acoustic parameters to measure the time needed for the sound pressure level to decay for 60dB in an enclosed space [27]. The measurement carried out in compliance with UNI EN ISO 3382 standard [14] applying the integrated impulse response method [15]. The indoor sound pressure level due to traffic noise is considerably reduced after the improvement of the façade acoustic insulation, while further treatments to indoor surfaces should be necessary to reduce internal reverberation time and to improve speech intelligibility [16].

For the background noise, it is the sound pressure level measured in the empty enclosed space with all the facilities like fans, HVAC system switched off. For the measurement of background noise, normally a class-1 sound level meter will be placed at 1.2 m from the ground, and it is at least 1m far from all the surfaces to make sure the sound will not block by the obstacles [14].

Clarity 50 is the early reflection of the sound energy measured in sound pressure level scale (dB) within the first 50ms that reflect back from the boundaries. It can be measured according to the UNI EN ISO 3382 [14] where a B&K type of 4128 HaTS placed at the lecturer's desk as the source of the sound. A class-1 sound level meter will put in the centre of the room as the receiver.

2.3 Past studies

Past studies on the classroom or room acoustic audio data put emphasis on some parameters like the reverberation time (RT), clarity (C50), Definition (D50), background noise (BN), and speech transmission index (STI) as mentioned in the Choi, Dongre et al., Gramez et al., Madbouly et al., Mealings et al., Pääkkönen et al., Peng et al., Pinho et al., and Sala et al. studies. The acoustics parameters are calculated from raw audio sound recordings.

Audio data analysis related to classroom acoustics were on the clearness and transmission level of the speech that can be listened by the students. For instance, Dongre and Patil presented in-situ objective acoustical measurements and assessment of acoustical characteristics for the analysis of the classroom acoustics of the Visvesvaraya National Institute of Technology (VNIT) located in Nagpur, India [2]. The analysis was based on in-situ measured indicators of room acoustic quality, such as reverberation time (RT30), clarity (C50), background noise (BN), and the speech transmission index (STI), to allow the identification of certain salient features of classroom acoustics [2].

Sala and Rantala concluded that only half of the classrooms have fulfilled the standard criterion for reverberation time and none of them fulfilled the acoustic standard criterion for acoustics measurements according to the Speech Transmission Index. In addition, background and activity noise levels were too high for speech communication, causing a risk of occupational voice disorders [3]. However, the background noise levels and acoustic properties of classrooms did not contribute to the noise level in this case.

Gramez and Boubenider, whereas, considered acoustic comfort for a conference room located in a sample of newly built public buildings. The important factors were the position of the machinery local and its defective design. The examples of defective designs are the modest acoustic performance of the terraced wall, reverberation, low volume and poor acoustic performance of the door opening directly onto the conference room [5].

Pääkkönen et al. presented the results of an acoustic performance evaluation of classrooms and their corridors on a test area of the Finnish Oulu Normal School. Two different acoustical setups were evaluated by measurements of the reverberation time, sound pressure level, and sound insulation [4]. Other acoustical parameters were also measured via sources of reverberation time to verify the difference of the test rooms; Speech Transmission Index (STI), disturbance radius (rD), spreading attenuation (D2,S), Clarity (C50), and Rapid Speech Transmission Index (RASTI). The measurements of noise were adhering to the Finnish guidelines while the measurements of reverberation time and sound insulation followed the International Standards ISO 140-4, ISO 140-5, ISO 717-1, and ISO 3382 [4].

Peng and Wang compared the before and after an acoustic treatment in an elementary-school classroom. Acoustic treatment was carried out by installing sound absorption materials on the ceiling of the classroom for control of sound reverberation. The effects of reverberation time on children's speech recognition have also been investigated [19]. After the classroom acoustic treatment, all the acoustic parameters like the subjective loudness of different types of noise sources, speech intelligibility were obviously improved.

Pinho et al. analyzed the most common problems that may affect the acoustic environment inside school building from classrooms' partition perspectives. Their study included measurement of reverberation time in classrooms; sound insulation between classrooms and between classrooms and corridors; impact sound insulation of floors and airborne sound insulation of façade [20]. The sound insulation of façade was made with all elements closed and with natural ventilation conditions (banners or windows tilt mode).

Choi concluded that the effect of the added absorption of occupants is dependent on the acoustical condition of the classroom. The changes in acoustical parameter values, due to added occupants in the classrooms, tended to be largest for the more reflective classrooms. The occupants may contribute to achieving ideal reverberation times (0.4 to 0.6 seconds) for speech in the more reflective classrooms, but not in the more absorptive classrooms [17].

Dongre et al. analysed based on in-situ measured indicators of room acoustic quality, such as reverberation time (RT30), clarity (C50), background noise (BN), and the speech transmission index (STI), permit the identification of certain salient features of classroom acoustics in a tropical climate like India and complementary practical challenges associated with natural ventilation. The paper concluded by outlining acoustic concerns observed in the objectively identified and investigated classrooms of a tropical climate of the representative case [2].

Madbouly et al. proposed new classroom acoustics assessment model (CAAM) based on analytic hierarchy process (AHP) for enhancing speech intelligibility and learning quality. The model is based on five main criteria that affect the learning process and related to classrooms acoustical properties. These include classroom specifications, noise sources inside and outside the classroom, teaching style, and vocal effort. The priority and weights of these major criteria along with their alternatives are identified using the views of students, staff, education consultants, and expertise by using a developed questionnaire, and the AHP methodology [10]. This model can be considered as a helpful framework enabling universities' decision makers to take effective decisions on classroom acoustics treatment issues. It also provides colleges' higher authorities the suitable guidelines that help for determining necessary requirements that help to raise the quality and efficiency of the educational environment; in order to reach an excellent learning environment; and hence increasing students learning outcomes [10].

Mealings et al. revealed much higher intrusive noise levels in the two largest open plan classrooms, resulting in signal-to-noise ratios and speech transmission index scores to be well below those recommended in classrooms with students of this age. Additionally, occupied background noise levels in all classrooms were well above recommended levels. These results suggest noise in classrooms needs to be better controlled, and open plan classrooms are unlikely to be appropriate learning environments for young children due to their high intrusive noise levels [18].

Eaton et al. had concluded that reverberation time (T60) and Direct-to-reverberant ratio (DRR) are important parameters which together can characterize sound captured by microphones in non-anechoic rooms [21]. These parameters are important in speech processing applications such as speech recognition and dereverberation. The values of T60 and DRR can be estimated directly from the acoustic impulse response (AIR) of the room. In practice, the AIR is not normally available, in which case these parameters must be estimated blindly from the observed speech in the microphone signal. The acoustic characterization of environments (ACE) challenge aimed to determine the state-of-the-art in blind acoustic parameter estimation and also to stimulate research in this area. A summary of the ACE challenge and the corpus used in the challenge is presented together with an analysis of the results. Existing algorithms were submitted alongside novel contributions, the comparative results of which are presented in this paper. The challenge showed that T60 estimation is a mature field where analytical approaches dominate whilst DRR estimation is a less mature field where machine learning approaches are currently more successful [21].

Salvador et al. figured out the statistical correlations between C80, STI, D50, EDT, RT and certain audio features have been analysed [22]. The Pearson, r values are above 0.8 in all cases. These high correlations enable acoustic parameters to be calculated from the musical characteristics of auralized audio signals [22].

Cerda et al. had determined the most representative acoustical parameters for halls intended for verbal or music audition. The impulse response at a great number of points was measured [23]. A group of orthogonal parameters was thus obtained, made up of three factors that group the parameters used by different outstanding researchers. These factors provide a clear acoustical interpretation. The optimal scores of these factors for different uses of halls make it possible to grade any hall, independently of its shape, for its corresponding use [23].

Antonello had investigated about room acoustics effects in the relationship between vowel height and vocal fry. Vocal fry has a significant high percentage for the low-height vowels compared with the high-height vowels ($\beta = 1.21$; standard error = 0.35), and for pink background noise present ($\beta = 0.89$; standard error = 0.35) compared with the condition without artificial noise added [28]. As the result, when the low-height vowels under the BN noise condition compared to the high eight one, the fry phonation are more likely to produced [28].

Jerlehag had do the research about the BN levels and noise sources in geriatric ward so the sound fields of the patient room can be examined. A-weighted equivalent (L_{Aeq}) and maximum Fast time-weighted sound pressure levels (L_{AFmax}) had been used as the parameters for the room acoustic measurement. It was found that the measured noise levels of the rooms exceeded the World Health Organisation's guide levels by at least 25 dBA of average levels and at least 10 dBA of the maximum noise level. Reverberation time (T_{20}) also measured at high frequencies in an empty six-bedded room was less than 0.8 s, whereas T_{20} at low frequencies was greater than 1.2 s [29].

Overall literature studies observed more efforts in the common study parameters used like reverberation time, clarity and speech transmission index in the classroom or lecture hall but lack in other parameters that also can potentially be used as the algorithm for the analysis like the initial time delay gap, spectral density, inter-aural cross-correlation coefficient and speech intelligibility index. Majority studies analyses the recorded data from statistical, modelling, simulation and data mining perspectives. No study reported classroom acoustics using data mining analysis. Therefore, in this study, the lacking acoustics parameters will be included in the data mining analysis.

Chapter Three: Research Methodology

3.0 Overview

This chapter presents the methods used in this project. The details of the methods used will be described. The research implementation is generally divided into four stages: Data Collection, Data Pre-processing, Data Classification and Knowledge Discovery (Figure 3.1). First stage involves experimental data collection whereby the lecture data will be recorded from the different lecture rooms. The collected audio data will be converted from the audio file into digitalized frequency response function file in numeric form at second stage. The useful attributes that include the location, room size, room's geometry and shape, number of seats, number of occupants, microphone position, number of electronic speakers, time, maximum volume frequency, minimum volume frequency, volume max, volume min, maximum noise volume, gender of the speaker, level of cohort, background noise (BN), reverberation time (RT), Clarity 50 (C50) and level of noise will be extracted recorded. The outliers and extreme values will be examined and rectified. In the third stage, the pre-processed data set will undergo data classification using the WEKA tool. All the WEKA available classifiers for this data set were applied for further analysis on the classifiers' performance. The classification patterns and correlation between the attributes were figured out for informative discovery.

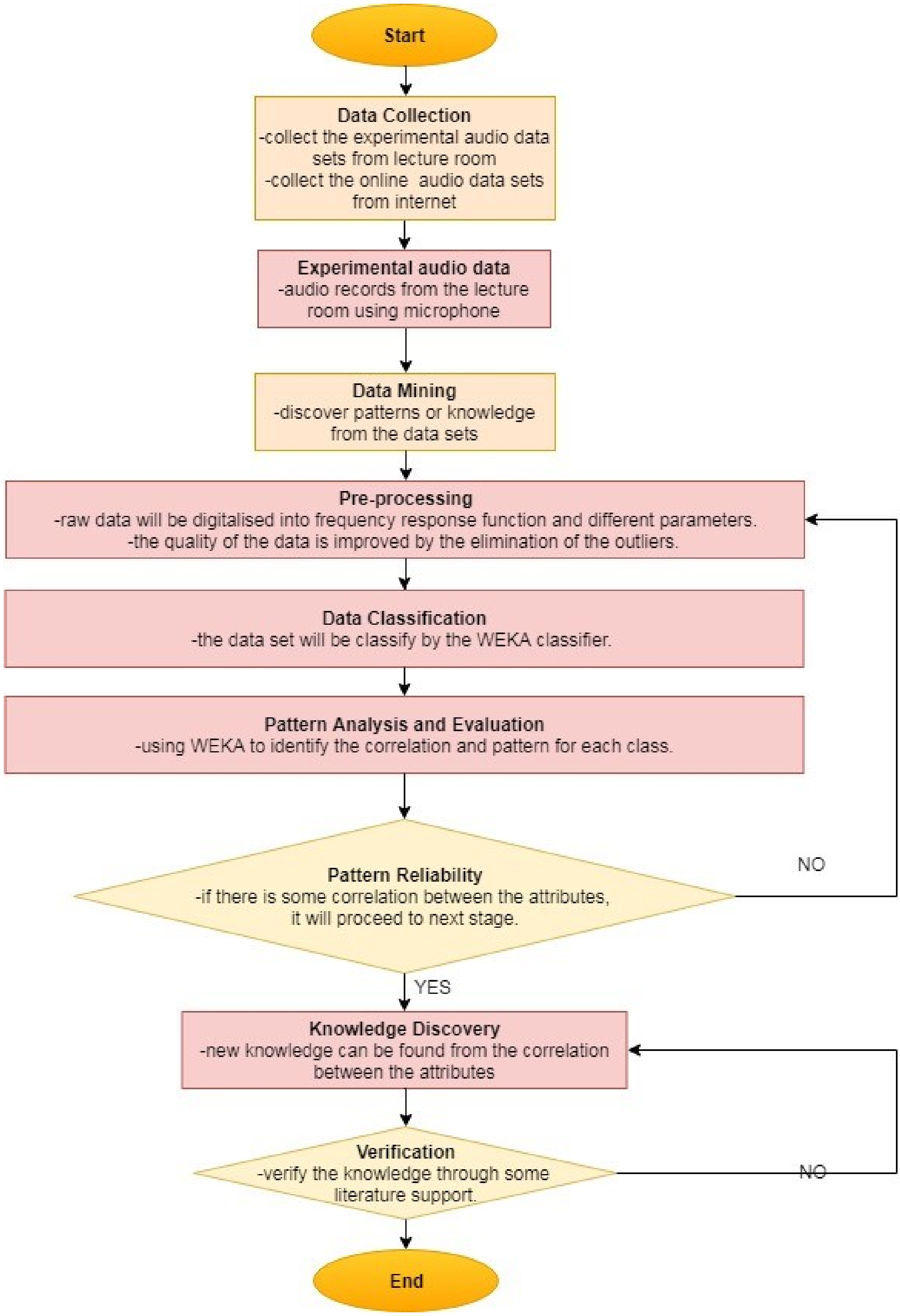

Figure 3.1: Flow chart of approach in classifying the lecture room acoustic.

3.1 Data collection

The project involves experimental data collection from the University Sains Malaysia's Engineering Campus three lecture rooms. There were five lecture room sizes in the University Sains Malaysia (USM) studied in this project. The lecture rooms targeted were lecture hall 1 (Dewan Kuliah 1), lecture hall 8 (Dewan Kuliah 8) and Mechanical School lecture room 1 (MEK 1) with specifications indicated in Table 3.1.

Table 3.1 Lecture room location and its specification

Room	Size	Specification
DK 1	50m x 28m (Large)	Maximum 1500 occupants, stepped profile, fan shape
DK 8	22.5m x 22.5m (Medium)	Maximum 350 occupants, stepped profile, fan shape
MEK 1	20m x 15m (Small)	Maximum 120 occupants, flat profile, rectangular shape

Four identical phones (iPhone 6 with built-in low-frequency roll off microphone) were used in this experiment to prevent biasness. . The four phones will be mounted on the phone holders at measured height approximately the height of students' ears about 1.2m from the ground (Figure 3.2). The microphones were faced towards the lecturer (speaker), to make sure same audio effect was received as the students' audio reception in the lecture rooms.

The position of the phones will be arranged according to the geometry and shape of the lecture room shown in Figure 3.3 and Figure 3.4. However, only four identical phones can be found. Therefore, the phones in position 1 and 6 will be removed because these two position audio data are not playing an important role for the data set, so only the position 2, 3, 4 and 5 will have the phones for recording.

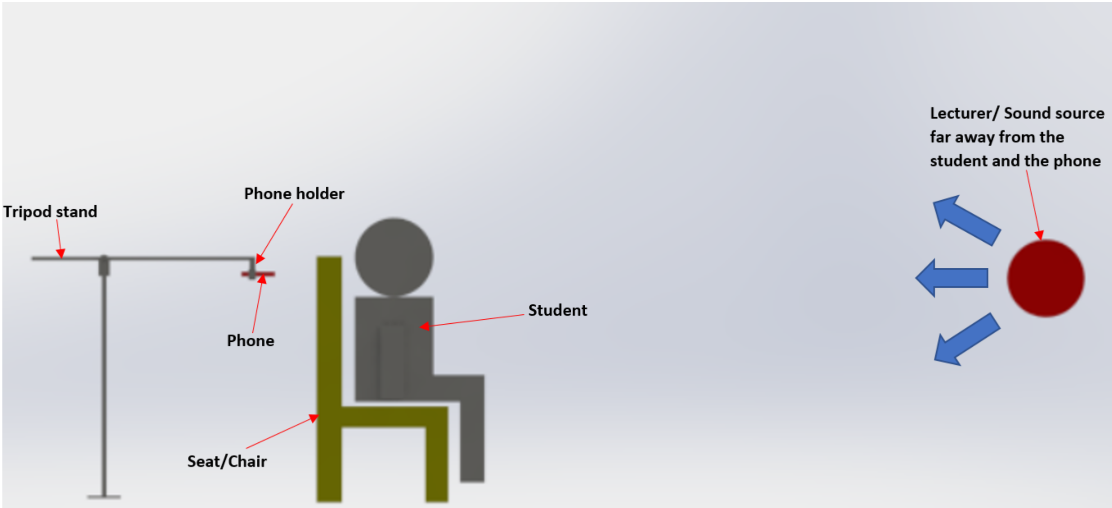

Figure 3.2: Set up for phone mounted on its holder with camera tripod stand.

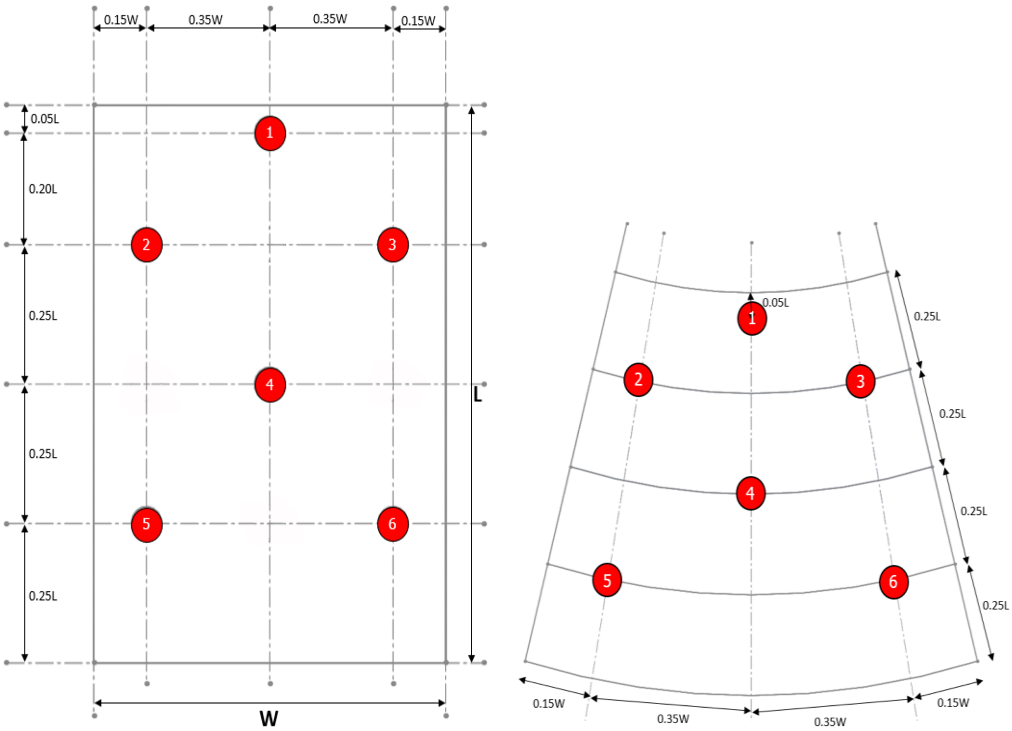

Figure 3.3: Microphones locations in the (a) rectangular shape (MEK 1) and (b) fan shape lecture room (DK 1 and DK 8).

3.2 Data pre-processing

The recorded raw data will be digitalised into the frequency response function and the relevant attribute data: time, maximum volume frequency, minimum volume frequency, volume max, volume min and maximum noise volume will be extracted using the Audacity Software (version 2.2.1). The data will be transformed into ".csv" file readable by the WEKA software.

The "Interquartile Range" filter had been used to eliminate potential extreme values and outliers based on equations (3.1) and (3.2). The outliers and extreme values can be determined using equation:

Outliers: $Q3 + OF*IQR < x <= Q3 + EVF*IQR$ Equation 3-1

$Q1 - EVF*IQR <= x < Q1 - OF*IQR$ Equation 3-2

Extreme values: $x > Q3 + EVF*IQR$ Equation 3-3

$x < Q1 - EVF*IQR$ Equation 3-4

where Q1 is the 25% quartile, Q3 is the75% quartile, IQR is the Interquartile Range, which can calculated by Q3 – Q1, OF is the Outlier Factor and EVF is the Extreme Value Factor. In the WEKA default setting, the Outlier Factor is 3 and Extreme Value Factor is 6.

For the Randomise filter, it is used as the mixer to mix up the data set in random sequence since the data collected is listed in time sequence. It can help to increase the reliability and performance of a classifier. In other words, whenever the 10-fold cross-validation is used, the test data will not have the specified or identical data on it.

3.3 Attributes

In order to measure the acoustic parameters for a lecture room, and to determine the noise level of the lecture room, some physical attributes for the lecture room like the room sizes, room geometry and shape, number of seats, number of electronic speakers and microphone position had been recorded. Other important attributes include the number of the occupants, the maximum and minimum volume frequency, strength, gender of the speaker, level of cohort also had been noted down. Other important room acoustic attributes like Clarity 50, background noise and reverberation time were also measured and calculated. The recorded raw data consisted of 19 attributes and 245 instances as summarized in Table 3.2.

Table 3.2 Attributes' description and data scale

Attributes	Instance	Remark
Location	{MEK1, DK8, DK1}	Name of the lecture room, 3 different lecture rooms.
Room Size	{S, M, L}	3 sizes which are small, medium and large.
Room Geometry and Shape	{P&R, S&F}	Plain profile and rectangular shape, Stepped profile and fan shape.
Number of Seats	[120, 350, 1500]	Seats available in the lecture room, the maximum students can fit inside during the lecture.
Number of Occupants	[34, …, 869]	Number of students during the lecture.
Microphone Position	{FL, FR, M, BL}	Position of the microphones located in the lecture room, which are front left, front right, middle and back left.
Number of Electronic Speakers	[2, 6]	Number of electronic speaker is used during the lecture.
Time	[3, 72]	The data taken from the Audacity every three minutes.
Maximum Volume Frequency	[3, …, 700]	Frequency when the volume reached maximum in audio frequency spectrum, in Hz.
Volume Max	[-50.6, …, 41.2]	Amplitude of the volume for the Maximum Volume Frequency, in dB.
Minimum Volume Frequency	[1108, …, 2000]	Frequency when the volume reached minimum in audio frequency spectrum, in Hz.
Volume Min	[-73, …, -46]	Amplitude of the volume for the Minimum Volume Frequency, in dB.
Maximum Noise Volume	[-32, …, -0.5]	The amplitude of noise for the 3 minutes interval, in dB.

Gender of Speaker	{M, F}	Male or female.
Level of Cohort	[100, 200, 400]	The course's cohort level.
Background Noise	[57, 61, 66]	Sound pressure level when no occupants inside and all the facilities in room is switched off.
Reverberation Time	[0.4, 0.6, 0.8]	Time for the sound pressure level to decay.
C50	[-2.6, -2.1, -1.4]	The early reflection of the sound from the obstacles within 50ms.
Level of Noise	{N, A, S}	Noisy, average and silence.

For the Maximum Noise Volume, it is determined through the Audacity software manually by crop the full audio data into 3 minutes interval audio data. The Maximum Noise Volume is the maximum volume amplitude within the 3 minutes data. The level of noise is determined according to the Maximum Noise Volume. When the MNV is less than -10dB, it will be classified as silence for the level of noise. When the MNV is greater or equal to -10dB until less than -5dB, it is classified as average level of noise. When the MNV is greater or equal to -5dB, the level of noise will be classified as noisy.

3.4 Data classification

In this study, the level of noise was defined as the class attribute whereby informative data patterns were categorized according to … algorithms built-in WEKA tool. There are 24 classifier algorithms adopted in this study for initial level classification on raw and pre-processed data (Table 3.1). The purpose is to find out which algorithm most reliable and best performed among all. The performance of the classification algorithm was evaluated on percentage of correctly classified instances.

In order to examine the contributions of the attributes towards data classification accuracies, the significant attribute analysis was performed. The significance of every single attribute from pre-processed data was used to classify data into important attributes and non-important attributes. This is to investigate its role and impact on the classification accuracy. Next, the best representative classifier will be picked from the rest based on several criteria consideration.

Table 3.3 Algorithm adopted at initial classification.

Classifier	Algorithms	Description
Tree	Decision Stump	Usually used in conjunction with a boosting algorithm. Does regression (based on mean-squared error) or classification (based on entropy). Missing is treated as a separate value.
	Hoeffding Tree	A Hoeffding tree (VFDT) is an incremental, anytime decision tree induction algorithm that is capable of learning from massive data streams, assuming that the distribution generating examples does not change over time.
	J48	Class for generating a pruned or unpruned C4.5 decision tree.
	LMT	Classifier for building 'logistic model trees', which are classification trees with logistic regression functions at the leaves. The algorithm can deal with binary and multi-class target variables, numeric and nominal attributes and missing values.
	Random Forest	Class for constructing a forest of random trees.

	Random Tree	Class for constructing a tree that considers K randomly chosen attributes at each node. Performs no pruning. Also has an option to allow estimation of class probabilities (or target mean in the regression case) based on a hold-out set (backfitting).
	REP Tree	Fast decision tree learner. Builds a decision/regression tree using information gain/variance and prunes it using reduced-error pruning (with backfitting). Only sorts values for numeric attributes once. Missing values are dealt with by splitting the corresponding instances into pieces.
Bayes	Bayes Net	Bayes Network learning using various search algorithms and quality measures. Base class for a Bayes Network classifier. Provides data structures (network structure, conditional probability distributions, etc.) and facilities common to Bayes Network learning algorithms like K2 and B.
	Naive Bayes	Class for a Naive Bayes classifier using estimator classes. Numeric estimator precision values are chosen based on analysis of the training data.
	Naive Bayes Multinomial	Multinomial naive bayes for text data. Operates directly (and only) on String attributes. Other types of input attributes are accepted but ignored during training and classification.
	Text	
	Naive Bayes Updateable	Class for a Naive Bayes classifier using estimator classes. This is the updateable version of Naïve Bayes. This classifier will use a default precision of 0.1 for numeric attributes when build Classifier is called with zero training instances.

Function	Logistic	Class for building and using a multinomial logistic regression model with a ridge estimator.
	Multilayer Perception	A Classifier that uses backpropagation to classify instances. This network can be built by hand, created by an algorithm or both. The network can also be monitored and modified during training time. The nodes in this network are all sigmoid except for when the class is numeric in which case the output nodes become unthresholded linear units.
	Simple Logistic	Classifier for building linear logistic regression models. LogitBoost with simple regression functions as base learners is used for fitting the logistic models. The optimal number of LogitBoost iterations to perform is cross-validated, which leads to automatic attribute selection.
	SMO	Implements John Platt's sequential minimal optimization algorithm for training a support vector classifier.
Lazy	Ibk	K-nearest neighbour's classifier. Can select appropriate value of K based on cross-validation. Can also do distance weighting.
	Kstar	K* is an instance-based classifier, that is the class of a test instance is based upon the class of those training instances similar to it, as determined by some similarity function. It differs from other instance-based learners in that it uses an entropy-based distance function.
	LWL	Locally weighted learning. Uses an instance-based algorithm to assign instance weights which are then used by a specified Weighted Instances Handler.

Rules	Decision Table	Class for building and using a simple decision table majority classifier.
	JRip	This class implements a propositional rule learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which was proposed by William W.
	OneR	Class for building and using a 1R classifier; in other words, uses the minimum-error attribute for prediction, discretizing numeric attributes.
	PART	Class for generating a PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule.
	ZeroR	Class for building and using a 0-R classifier. Predicts the mean (for a numeric class) or the mode (for a nominal class).

3.5 Knowledge discovery

It was anticipated that the most impactful attributes to the data set will be retrieved concerning about the lecture room sizes toward the room acoustics attributes and the effect on background noise and activities noise inside the lecture room. It can be predicted that the dimension of lecture room will affect the reverberation time and clarity 50 of the room. Those two attributes are the main elements of the speech transmission index (STI). When the reverberation time decrease and clarity 50 increase, the STI for the lecture room will increase and it means the learning condition inside the lecture room will become better.