Identification of Material Surface Features using Gray Level Co-Occurrence Matrix and Generalized Regression Neural Network

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Abstract—**This paper describes a practical system that was developed to identify material surfaces in order to obtain its absorption coefficient values without using complicated and time-consuming procedures and expensive physical equipment to get the measurements. The system is divided into two subsystems which are subsystem 1, by extracting material surface images by using the Gray Level Co-occurrence Matrix (GLCM) to produce four Haralick coefficients, which is used by subsystem 2 that uses Generalized Regression Neural Network (GRNN) to classify the surfaces. Four types of material surfaces are captured and a total number of 280 images used as the input. It is concluded that the system for identification of material surfaces using GLCM and GRNN was successfully developed.**

Keywords—GLCM; GRNN; absorption coefficient; material surface; GUI

I. Introduction

The reverberation time (RT) could be predicted by using two parameters which are absorption coefficient and also the dimensions of the room. There are some careers that related to the sound absorbent in a room and yearn for a good sound absorber so that the information given will be received by the listener. Reverberation somehow could disturb the smoothness for the sound to arrive to the listener. In order to measure the absorbance, it is necessary to perform physical measurement that used expensive equipment and complicated procedures.

The main purpose of this study is to develop a practical system that could identify the absorption coefficient parameters in the acoustic room without using such complicated physical measurement. This study proposed a practical system using two subsystems; subsystem 1 is the Gray Level Co-occurrence Matrix (GLCM) method and subsystem 2 is the Generalized Regression Neural Network (GRNN) method which the input is the photographic image.

Photographic image would have the texture needed by the subsystem 1 in order to extract the features. The tone of the image is strongly related to the texture of the image because tone and texture always present in an image [1]. The image classification using GLCM need the image to have the “grey-tone spatial-dependence matrix” that come along with the 14 coefficients that can be derived from the texture [2].

The photographic images of material surfaces of classroom captured by a digital signal-lens reflex (DSLR) camera needs by the subsystem 1 to extract the material surface features. The GLCM method could be used to obtain the absorption coefficient by extract out Haralick’s coefficient. There are 14 Haralick’s coefficients but only four common coefficients used, which are contrast (cont), correlation (corr), angular second moment (asm) and homogeneity (hom) [1]. GLCM is the different combination of gray levels occurs in the images given in the form of matrixes [2], [3].The size of test images can also be a cell of 8 x 8 pixel size that will allow the GLCM sense effectively to very details of the interest [4], [5].

Absorption coefficient determines how far the sound incident can pass through material until it is totally absorbed and depends on the typed of the material itself. Some of the sound incident did hit the surface and reflected and some of it did absorb into the material. Absorption coefficients affect the ability of the sound to arrive to the receiver from the source. There are several reports that proposed other techniques for predicting the absorption coefficient without using the physical measurement [3], [6], [7], [8].

High absorption coefficient allows the material to effectively absorb sound and the sound will clearly arrive to the receiver. Meanwhile, low absorption coefficient will result sound to reverberate into the classroom. There are existing physical measurements such as impedance tube method and reverberation room method, but these two measurements need special and expensive equipment with complicated procedures and skills. The costing are unbearable and the time consumed are much longer because it need the acoustic specialist to carry the measurement out.

There is also a study regarding the estimation of the absorption coefficient by employing the artificial neural network (ANN) algorithm using different perforated wooden panels, but it need various setting combinations such as the perforation percentage, backing material and thickness of the wooden panels [6]. Paper by Hodgson and Scherebnyj used the measurement of early decay time and multivariable linear-regression techniques in order to estimate the 125-8000 Hz octave-band sound absorption coefficient. For the ANN algorithm, the author did use eight surfaces in the classroom [7]. In this paper however, another approach by using photo images as inputs to estimate the absorption coefficient was proposed.

From the absorption coefficient obtained, the system will then proceed to the subsystem 2 which is the GRNN method that will be used to train the data obtained from subsystem 1.

II. THEORITICAL DESCRIPTION

A. Image Texture

In order to identify the object or material, texture is one of the crucial features that could be used to recognize the type of object. Between two different textures obtained, there have different features unless it was the same texture. It will be easier to differentiate the textures using the information contained because it has various methods such as geometric, random field, fractal and signal processing models that could extract the assort of textural characteristic from the images [1].

Image texture is defined as a function of the spatial variation in pixel intensities. The function is the gray values that useful for many applications and been a subject for study by researcher [1]. Textures have many types which the textures could be fine, coarse, smooth, rippled, or linear [2].

From the texture, there are many types of information that could be obtained, such as dimension and absorption coefficients. The example of features in a dimension that can be acquired are size, shape, color and orientation of the elements of the pattern and it differ between two image textures.

B. Gray Level Co-occurrence Matrixes (GLCM) Implementation

GLCM defined as “A two dimensional histogram of gray levels for a pair of pixels, which separated but a fixed spatial relationship” [1]. GLCM is a method used to generate the texture into different texture synthetically. The image of material surfaces obtained from image capturing used in the system, but theoretically, it uses the two pixels of reference and neighboring technique to determine the reference pixel value.

In the other hand, the reference pixels are set by using the immediate neighbor. The immediate neighbor is the two pixels from a square matrix with size determined according to gray levels of pixels of an image which are computed at a certain distance, *d* and angle, θ ($\theta = 0^o, 45^o, 90^o, 135^o$) as in Fig.1. O is denoted as the origin of pixel [3].

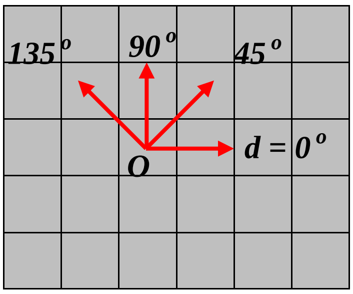


Figure 1. Levels of Pixels [3]

C. Generalized Regression Neural Network (GRNN)

GRNN variant comes from the radial basis network (RBF), which require more neurons than standard Feedforward Backpropagation networks, but often can be designed at a fraction of the time it takes to train standard Feedforward networks. The other one variant of RBF is the probabilistic neural networks (PNN) [10]. One of the disadvantages of the GRNN and PNN method is both of the methods are slower to execute more computation used compared to other networks for the approximation and classification functions [10].

GRNN is a kind of radial basis network that is often used for function approximation and has a radial basis layer with a special linear layer. The architecture for the GRNN is similar to the RBF but has a slightly different second layer [10]. GRNN is basically based on the statistical principles and converges asymptotically with increasing number of samples to achieve optimization of the regression surface [11].

III. SYSTEM DEVELOPMENT

A. Subsystem 1: GLCM

GLCM is a common technique in image processing used for texture measure. From the GLCM obtained, around 14 features can be extracted as proposed by Haralick[1]. However, this paper only includes the most commonly used features which are Contrast, Correlation, Angular Second Moment and Homogeneity. The block diagram for GLCM is shown as in Fig. 2. While, flowchart for GLCM programming code is shown as in Fig. 3. The programming code was separated into three paragraphs and each of the paragraphs executes the image of material surfaces, converts to gray scale image and obtained the Haralick’s coefficient, respectively.

B. Subsystem 2: GRNN

GRNN input was the values of the four coefficients developed by GLCM method that extracted from the material surfaces images which are contrast, correlation, ASM and homogeneity. The value of absorption coefficients was referred to the relevant reference shown in Table 1 [12]. Flowchart for the subsystem 2, GRNN programming code is shown as in Fig. 4.

Figure 2. GLCM Block Diagram

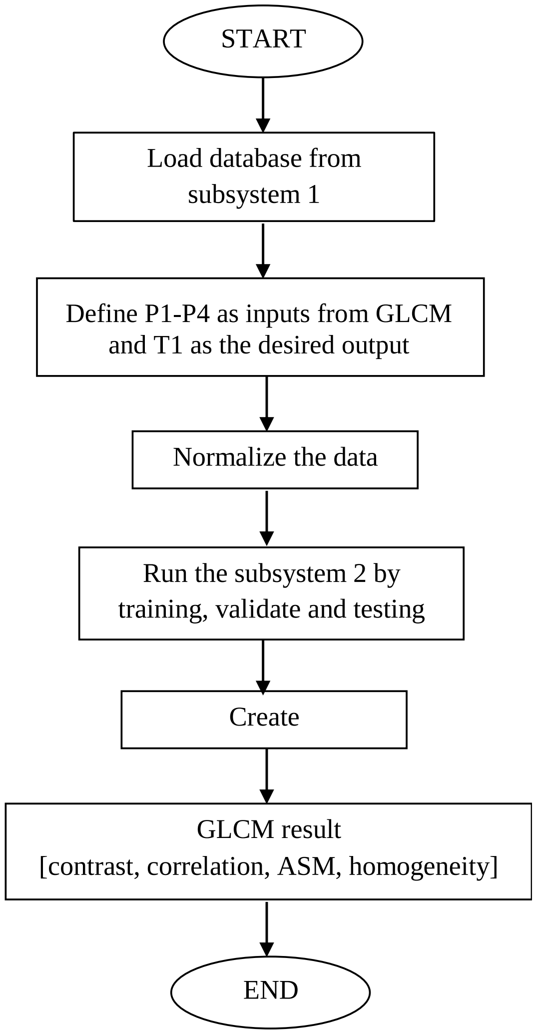


Figure 3. Flowchart for GLCM Programming Code

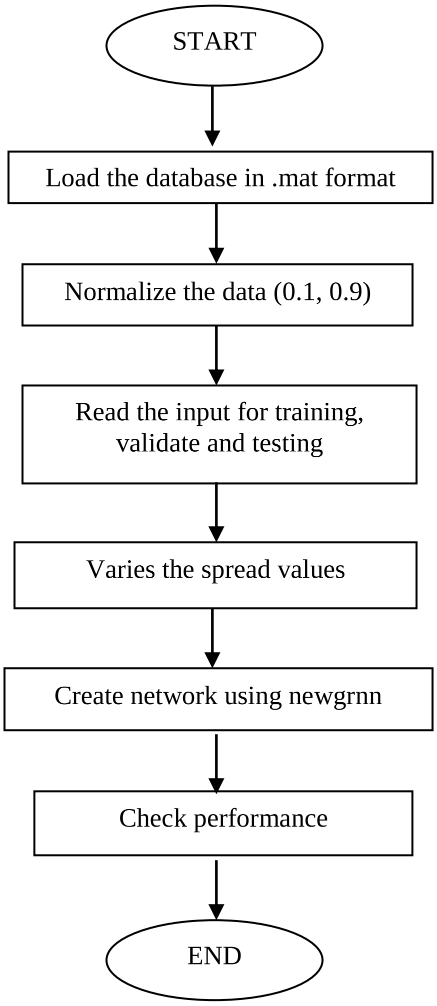


Figure 4. Flowchart for GRNN Programming Code

TABLE 1. ABSORPTION COEFFICIENT FOR EACH MATERIAL SURFACE BY FREQUENCY

Type of surfaces	Absorption coefficient					
	125Hz	250Hz	500Hz	1kHz	2kHz	4kHz
Concrete wall	0.10	0.05	0.06	0.07	0.09	0.08
Floor	0.02	0.03	0.03	0.03	0.03	0.02
Wooden wall	0.15	0.11	0.10	0.07	0.06	0.07
Ceiling	0.15	0.11	0.04	0.04	0.07	0.08

C. *Graphical User Interface (GUI)*

GUI programming code has three main components which are initialization GUI, load image, classified material surface and absorption coefficient button code, respectively.

IV. RESULT AND ANALYSIS

This subsection is divided into two parts. The first part is the result for subsystem 1 using GLCM and the second part is the result for subsystem 2 using GRNN.

A. *Subsystem 1:GLCM*

In the database, the total of the material surface images are 280 and were fed into GLCM and Haralick coefficient analysis to obtain the four coefficients. Table 2 - 5 shows the maximum and minimum extracted input values from the four material surface images in the database. From the tables, the maximum and minimum values are different for each coefficient and the network used these differences to identify each surface.

TABLE 2. CONCRETE WALL CLASSIFICATION

	Minimum	Maximum	Surface
Contrast	0	0.1599	1
Correlation	0.1608	0.9259	
ASM	0.3932	0.9999	
Homogeneity	0.9201	0.9999	

TABLE 3. FLOOR CLASSIFICATION

	Minimum	Maximum	Surface
Contrast	0.0324	0.1196	2
Correlation	0.5209	0.8707	
ASM	0.4104	0.8362	
Homogeneity	0.9402	0.9838	

TABLE 4. WOODEN WALL CLASSIFICATION

	Minimum	Maximum	Surface
Contrast	0	0.0671	3
Correlation	0.3649	0.9148	
ASM	0.4379	0.9999	
Homogeneity	0.9664	0.9999	

TABLE 5. CEILING CLASSIFICATION

	Minimum	Maximum	Surface
Contrast	0.0001	0.1484	4
Correlation	0.5339	0.9234	
ASM	0.4427	0.9998	
Homogeneity	0.9258	0.9999	

B. Subsystem 2: GRNN

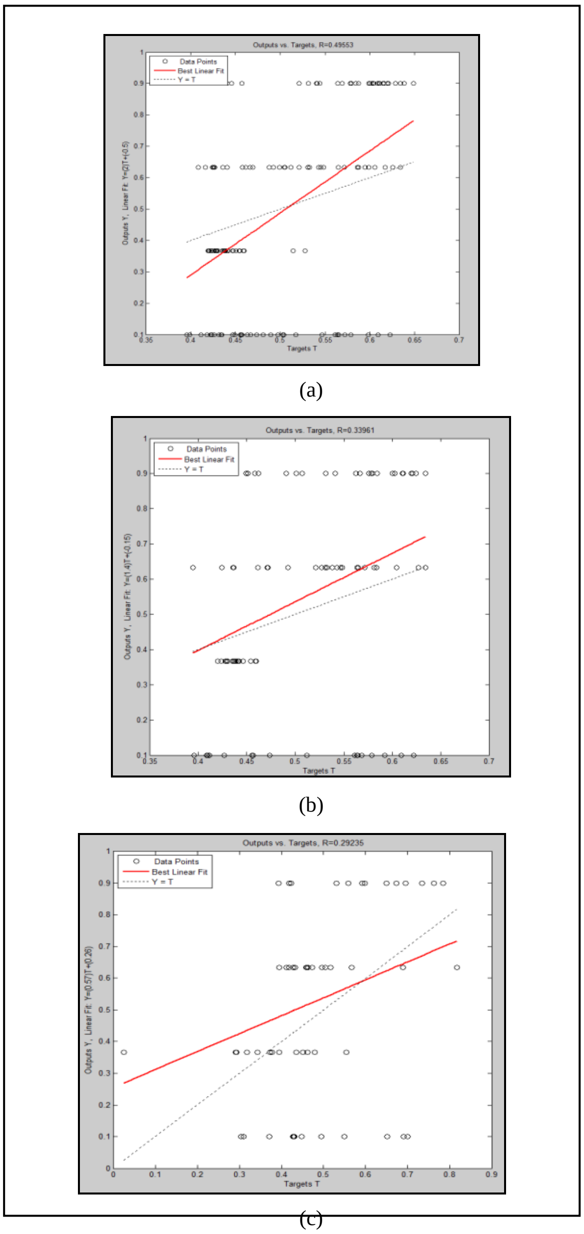
In the GRNN method, there are 19 numbers of the spread used between 0.1 until 1.0 with range of 0.05. The dataset is divided randomly with 60% for testing, 20% for validation, and the other 20% for testing. Validation data are important to make sure overfitting did not occur. Testing data used only for testing the final solution in order to confirm the predictive power of the network. Training data must be more than validation and testing data to ensure that each type of texture is trained.

TABLE 6. PERFORMANCE FOR EACH VALUE OF SPREAD

No.	Spread	Elapsed time (s)	Performance		
			Training	Validation	Testing
1	0.1	14.00837	7.21E-02	6.66E-02	7.62E-02
2	0.15	13.60469	7.96E-02	7.69E-02	6.54E-02
3	0.2	25.606847	5.89E-02	7.33E-02	1.08E-01
4	0.25	16.461832	7.77E-02	7.64E-02	9.23E-02
5	0.3	27.343885	6.47E-02	8.19E-02	8.65E-02
⋮	⋮	⋮	⋮	⋮	⋮
15	0.8	18.345283	8.41E-02	7.77E-02	7.71E-02
16	0.85	26.769678	7.78E-02	7.25E-02	9.07E-02
17	0.9	14.546417	9.01E-02	8.58E-02	8.54E-02
18	0.95	29.011723	7.90E-02	7.15E-02	9.03E-02
19	1	35.268165	7.50E-02	8.16E-02	8.16E-02

For each number of spread the Mean Square Error (MSE) values for training, validation and testing are different. From the GRNN results, the lowest value for the MSE is consider the best result. The elapsed time is the time taken for the iteration to finish until the highest validation.

Table 6 shows the performance for each value of spread. The lowest MSE for testing is 0.0654 using 0.15 spread values. For testing, the data used had never been encountered by the network before. Hence this spread value give the best result for new data to be classified. Fig. 5 shows the regression values for training, validation, and testing are 0.49553, 0.33961 and 0.29235 respectively using spread value of 0.15.



(a)

(b)

(c)

Figure 5. Regression between Output Y and Target T for spread value of 0.15 where (a) Training, (b) Validation and (c) Testing

Using the spread value of 0.15, the final network was produced where this network is capable of classifying each material surface from the provided material surface photo image. The final network is lastly fed to the system for the final product.

C. Graphical User

Graphical User Interface (GUI) is a program interface that contained the computer's graphic capabilities in order to ease the user to use the developed system. GUI is implemented in the system for a simple and easier approach to users. The interface for GUI used for the system is shown in Fig. 6.

After the network is able to identify the correct material surface, the corresponding absorption coefficient from Table 1 will be shown on the GUI.

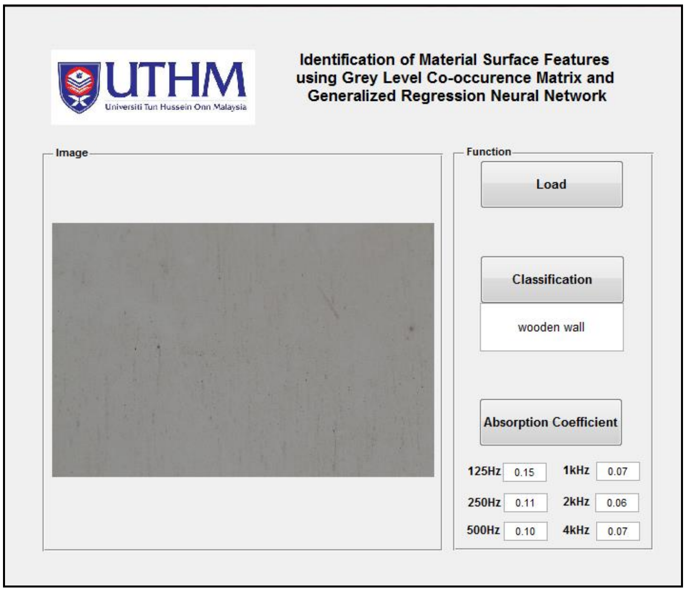


Figure 6. GUI for proposed system

V. CONCLUSION

Identification of material surface features using two subsystems, GLCM and GRNN were successfully developed. The developed system is able to identify the material surface; concrete wall, floor, wooden wall and ceiling, with the lowest testing MSE of 0.0589 using 0.15 spread value. A simple GUI is used for the final interface of the system where all the absorption coefficient values will be displayed after the system has successfully identify the corresponding surface.

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