PRACTICAL SUBSYSTEMS TO IDENTIFY ROOM DIMENSIONS AND MATERIAL SURFACES USING PHOTOGRAPH IMAGES FOR ROOM ACOUSTIC SIMULATIONS

画像処理技術の利用による音場シミュレーションのための境界条件の簡易測定システム

Musli Nizam BIN YAHYA — * 1,6 Toru OTSURU — * 2
Reiji TOMIKU — * 3 Takeshi OKUZONO — * 4
Toshiki NAGASAWA — * 5 Tomohiro ODA — * 5

ムスリ ニザム ビン ヤハヤ — * 1,6 大鶴 徹 — * 2
富来礼次 — * 3 奥園 健 — * 4
長澤利喜 — * 5 小田智弘 — * 5

Keywords:

Feed Forward Neural Network (FFNN), Gray Level Co-occurrence Matrix (GLCM), Photographic image, Material surface, Dimension

キーワード:

フィード フォワード ニューラルネットワーク, 濃度共起行列, 写真画像, 材料表面, 寸法

A practical technique for simulating room acoustics parameters is proposed. The technique comprises Subsystems 1 and 2, each of which uses photographic images. Subsystem 1 uses a Gray Level Co-occurrence Matrix and a Feed Forward Neural Network to identify material surfaces. Subsystem 2 uses a Dimension Vision Predictor with the author's "ruler method" to identify the dimensions. Examinations conducted in practical rooms revealed good correlation coefficients of $r \geq 0.90$ for Subsystem 1 and $r \geq 0.99$ for Subsystem 2. Finally, simulations of reverberation times were conducted using Finite Element Analysis (FEA) with identified parameters. Sufficient agreement was confirmed.

1. Introduction

Absorption coefficients and dimensions of a room are important parameters that are useful to identify the sound fields of a room (e.g., reverberation time, RT) that are necessary for use with theoretical techniques such as Sabine's or Eyring's formula and in computational techniques such as Ray-Tracing and Finite Element Analysis.

Generally, an absorption coefficient is obtained from physical measurements (e.g., impedance tube method and reverberation room method) that require special equipment and skills. Therefore, several reports^{1,2)} have proposed new techniques for identification of the absorption coefficient without using physical equipment.

Dimensions are obtained from physical measurements such as laser or tape measurements. CAD drawings can give room dimensions but it remains necessary to take measurements in situations where no drawing is available. Lately, 3D scanner technology is widely used to estimate room dimensions. Although such scanners provide precise measurements, they are expensive and require long the post processing.

Aiming for practical applications to identify parameters of rooms, two simple subsystems using photographic images are proposed here. Three techniques are used to build the subsystems: i. a Gray Level Co-occurrence Matrix

(GLCM); ii. a Dimension Vision Predictor (DVP); and iii. a Feed-Forward Neural Network (FFNN). These techniques yield two subsystems. Subsystem 1 uses GLCM and FFNN to identify room material surfaces. By identifying those materials, corresponding absorption coefficients are also given. Subsystem 2 uses DVP to identify room dimensions.

The accuracy of the two subsystems is examined using actual rooms to investigate the identification capability of two subsystems. The absorption coefficients and dimension identification from two subsystems are used to compute RTs of actual rooms using Finite Element Analysis (FEA). The computed RTs are then compared with RTs by FEA using actual absorption coefficients and dimensions.

Using these subsystems, we can ascertain room parameters easily, rapidly, and at a low cost compared using physical measurement. The subsystems are useful for researchers, practical engineers, and designers to estimate sound fields of existing rooms.

2. Theoretical Description

2.1. Gray Level Co-occurrence Matrix (GLCM)

The GLCM technique has been implemented successfully in texture feature analysis to analyze texture features of an image³⁾. To date, no reported study has applied GLCM to acoustic fields.

^{*1} Graduate Student, Graduate School of Eng., Oita Univ.

^{*2} Prof., Dept. of Arch. and Mech., Oita Univ., Dr. Eng.

^{*3} Assoc. Prof., Dept. of Arch. and Mech., Oita Univ., Ph. D.

^{*4} Post Doctoral Fellow, Graduate School of Eng., Oita Univ., Ph. D.

^{*5} Graduate Student, Graduate School of Eng., Oita Univ.

^{*6} Dept. of Mechanics, UTHM, Malaysia

^{*1} 大分大学大学院工学研究科 博士後期課程
(〒 870-1192 大分市旦野原 700 番地)

^{*2} 大分大学工学部 教授・工博

^{*3} 大分大学工学部 准教授・博士 (工学)

^{*4} 大分大学工学部 博士研究員・博士 (工学)

^{*5} 大分大学大学院工学研究科 博士前期課程

^{*6} Dept. of Mechanics, UTHM, Malaysia

Fig. 1. Computed GLCM. (a) Gray level of an image (b) GLCM for element $P_{1,0^\circ}(3,0)$ and at $P_{1,90^\circ}(2,2)$.

A GLCM is generated from a square matrix (Ng) with size determined according to the gray levels of pixels of an image that can be captured using a digital camera. An image includes numerous pixels, each of which presents a level of gray. A square matrix Ng is formed at these pixels.

A GLCM comprises numerous elements, each designated as probability $P_{d,\theta}(i,j)$. The $P_{d,\theta}(i,j)$ represents pixels with gray levels i and j , which are counted at certain distance d (e.g. $d = 1$ or 2) and direction angle θ ($\theta = 0^\circ$, 45° , 90° and 135°) between the two image pixels. Haralick⁴⁾ provides addition explanation of GLCM.

Figure 1 presents an example of computation of the GLCM with size $i = 3$ and $j = 3$. Here, i and j are taken from the gray level of an image. To count probability $P_{1,0^\circ}(3,0)$, by reference to Fig. 1(a), it is three intensities of pair pixels ($i = 3, j = 0$) at distance of two pixels $d = 1$; direction angle θ is counted as 0° . A similar process can be conducted at $P_{1,90^\circ}(2,2)$. The intensity at that probability is 2.

Generally, it is difficult to implement GLCM directly. Therefore, Haralick proposed 14 coefficients of texture features. The four commonly used Haralick coefficients are listed below.

$$cont = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P_{d,\theta}(i,j) \cdot (i-j)^2 \quad (1)$$

$$corr = \frac{\left\{ \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P_{d,\theta}(i,j) \cdot (i,j) \right\} - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (2)$$

$$ASM = \sum_{i=0}^{Ng-1} \sum_{j=1}^{Ng-1} \{P_{d,\theta}(i,j)\}^2 \quad (3)$$

$$hom = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \frac{P_{d,\theta}(i,j)}{1+(i-j)^2} \quad (4)$$

In those equations, $cont$ is the contrast used to measure the image contrast, $corr$ is the correlation used to measure image linearity, and ASM is the angular second moment used to measure image smoothness. Also, hom represents the homogeneity used to indicate homogeneity in uniform images. In addition, μ_x , μ_y , σ_x , and σ_y are the respective means and standard deviations of the probability matrix of GLCM obtained by summing the row.

2.2. Feed Forward Neural Network (FFNN)

Fundamentally, FFNN architecture involves three

Fig. 2. Architecture of FFNN.

layers: the input layer, hidden layer, and output layer. Each layer consists of numerous nodes, forming a network connection, as presented in Fig. 2.

The FFNN can be interpreted using the following equations.

$$v_j = \sum_{i=1}^m I_i w_{ij} + \theta_j \quad (5)$$

$$a_j = \varphi(v_j) = \frac{1}{1 + \exp(-v_j)} \quad (6)$$

$$O_k = \varphi(v_k) = \sum_{j=1}^n w_{jk} a_j + \theta_k \quad (7)$$

$$E = \frac{1}{N} \sum_{r=1}^N (D_r - O_r)^2 \quad (8)$$

Therein, E is an error term, D_r stands for a desired value (target), and O_r represents the output signal (network output), N signifies the number of samples, v_j is the summation of I_i (input signal), w_{ij} denotes a weight value between the input and hidden layer, and θ_j represents the bias/threshold at j th. Furthermore, a_j signifies the output of the hidden layer, $\varphi(v_j)$ denotes the transfer function (sigmoid function) associated with node j in the hidden layer, O_k represents the output of the output layer, $\varphi(v_k)$ stands for the transfer function of the output layer, but in this case, we used a linear function ($\varphi(v_k) = v_k$). Other variables are w_{jk} , which is the weight value between hidden and output layers, θ_k is the bias at output layer, and i, j , and k respectively denote the input nodes ($i = 1, \dots, m$) in the input layer, ($j = 1, \dots, n$) are the hidden nodes in the hidden layer, and ($k = 1$) is the output node in the output layer.

Before implementing the FFNN, a database to be analyzed is transformed (0.1–0.9) to standardize the range. Overlearning occurs during the FFNN learning process. To surmount the problem, a database is divided into three subsets: a training subset, a validation subset, and a test subset. The training subset is used to train the FFNN. The validation subset is used to validate the learning process, and the test subset is used to investigate the prediction performance. The proportion of each subset is chosen randomly. To obtain the optimum network, 2–15 hidden nodes are used. The mean square error (MSE) and

Fig. 3. Principle of stereo vision

correlation coefficients (r) are used for assessment.

2.3. Dimension Vision Predictor (DVP)

Several techniques are used to measure dimensions using a camera. Some techniques demand special equipment and camera lens calibration. Therefore, aiming at practical use, this study chooses survey-from-photo⁵⁾ because it can be implemented directly from any ordinary camera without calibrating the camera lens.

Generally, survey-from-photo identifies the dimension based on two images. The images are marked with two corresponding points. Then both are connected to make a line at an object to measure. A reference dimension is necessary to achieve an accurate measurement. The reference dimension is a dimension obtained from an object that is known exactly. Here, survey-from-photo uses that object dimension as a reference to standardize the scale range to the images.

The basic concept of survey-from-photo is that of the "stereo vision" principle, which uses two cameras to measure dimensions of an object, as presented in Fig. 3. One camera is located at C_r and another at C_l with intervening distance (d). The cameras are focused at point $P_1(x_1, y_1, z_1)$ and $P_2(x_2, y_2, z_2)$ with certain focus length (f), which are all obtainable at the camera lens. At f , two image points are apparent at the image P_{1r} , P_{1l} , P_{2r} , and P_{2l} with respective coordinates (x_{1r}, y_{1r}) , (x_{1l}, y_{1l}) , (x_{2r}, y_{2r}) , and (x_{2l}, y_{2l}) . The coordinates (x_{1r}, y_{1r}) , (x_{1l}, y_{1l}) , (x_{2r}, y_{2r}) , and (x_{2l}, y_{2l}) are calculable by considering the center of image as the origin. To obtain the coordinate of $P_1(x_1, y_1, z_1)$ and $P_2(x_2, y_2, z_2)$, the equation is definable simply as shown below.

$$\text{The } P_1(x_1, y_1, z_1); \begin{pmatrix} x_1 \\ y_1 \\ z_1 \end{pmatrix} = \frac{d}{x_{1l} - x_{1r}} \begin{pmatrix} x_{1l} \\ y_{1l} \\ f \end{pmatrix} \quad (9)$$

$$\text{The } P_2(x_2, y_2, z_2); \begin{pmatrix} x_2 \\ y_2 \\ z_2 \end{pmatrix} = \frac{d}{x_{2l} - x_{2r}} \begin{pmatrix} x_{2l} \\ y_{2l} \\ f \end{pmatrix} \quad (10)$$

$$L_x = d \left(\frac{x_{1l}}{x_{1l} - x_{1r}} - \frac{x_{2l}}{x_{2l} - x_{2r}} \right) \quad (11)$$

$$L_y = d \left(\frac{y_{1l}}{x_{1l} - x_{1r}} - \frac{y_{2l}}{x_{2l} - x_{2r}} \right) \quad (12)$$

Fig. 4. Sample images of material surfaces for (a) wall, (b) door, (c) floor, (d) window, (e) ceiling, and (f) carpet.

$$L_z = df \left(\frac{1}{x_{2l} - x_{2r}} - \frac{1}{x_{1l} - x_{1r}} \right) \quad (13)$$

In those equations,

$$x_{1l} = \frac{f}{\tan \theta_{P_{1l}}} \quad (14) \quad x_{2l} = \frac{f}{\tan \theta_{P_{2l}}} \quad (15)$$

$$x_{1r} = \frac{f}{\tan \theta_{P_{1r}}} \quad (16) \quad x_{2r} = \frac{f}{\tan \theta_{P_{2r}}} \quad (17)$$

the distance (L) between P_1 and P_2 can be expressed as

$$L = \sqrt{L_x^2 + L_y^2 + L_z^2} \quad (18)$$

Using the reference scale (L), DVP is identifiable by coordinates at P_{1r} , P_{1l} , P_{2r} , and P_{2l} by clicking the mouse.

2.4. Finite Element Analysis (FEA)

The FEA numerical technique, well known in acoustical fields, has been used in many fields to obtain the sound field of a room with high accuracy^{6,7)}. The FEA method used for this study was time domain analysis.

The FEA procedure is based on the principle of the minimum of total potential energy applied to a three-dimensional sound field. The discretized equation for a sound field in the frequency domain is expressed as

$$(\mathbf{K} + i\omega\mathbf{C} - \omega^2\mathbf{M})\mathbf{p} = i\omega\rho v_0\mathbf{W} \quad (19)$$

where $\mathbf{M}$, $\mathbf{C}$, and $\mathbf{K}$ respectively signify the acoustic mass, dissipation, and stiffness matrices. Furthermore, i , $\mathbf{p}$, ρ , ω , v_0 , and $\mathbf{W}$ respectively denote the imaginary unit ($i^2 = -1$) sound pressure vector, the air density, angular frequency, velocity of sound vibration and distribution vector. By assuming that $\cdot$ and $\ddot{\cdot}$ are first-order and second-order derivatives in time, the semi discrete equation in time domain can be evaluated using Eq. (20) shown below.

$$\mathbf{M}\ddot{\mathbf{p}} + \mathbf{C}\dot{\mathbf{p}} + \mathbf{K}\mathbf{p} = \rho v_0\mathbf{W} \quad (20)$$

Time domain analysis is described elsewhere by one of

the authors⁸⁾.

3. Subsystem 1

3.1. Methodology of Subsystem 1 Development

3.1.1. Material Surface Capturing

For this study, six material surfaces were taken of Oita University rooms, as portrayed in Fig. 4. Surfaces (a), (b), (c), (d), (e), and (f) are, respectively, surfaces for walls, doors, floors, windows, ceilings, and carpets. To perform material surfaces capturing, an ordinary camera is useful. Regarding standardization of images, a digital single-lens reflex (DSLR) camera with Sigma 50 mm f2.8 lens was used. In addition, the distance from the camera to the surface material was set to 40 mm with autofocus mode, whereas the respective lens settings for aperture, shutter speed and ISO speed were f2.8, 1/80, and 100. To analyze the accuracy of Subsystem 1, 368 images of surfaces were captured at different locations in three rooms. The proportions of images of material surfaces are: surface (a) = 69 images, surface (b) = 71 images, surface (c) = 66 images, surface (d) = 56 images, surface (e) = 67 images, and surface (f) = 40 images. All images were analyzed using GLCM.

3.1.2. GLCM Implementation

The GLCM was computed for the 368 images of surface materials using the following settings: i. $d=1, \theta=0^\circ$; ii. $d=1, \theta=45^\circ$; iii. $d=1, \theta=90^\circ$; and iv. $d=1, \theta=135^\circ$. Each Haralick's coefficient provides four values based on settings, but only an average value of four values is considered hereinafter. The average value is designated as the coefficient value for this study. Because of variations of brightness and texture features in our experiment, the ranges of the coefficient values become too wide to be processed. To overcome this problem, a limitation for each coefficient value was made using the means ($\bar{x}$) and standard deviation (σ). The limitations are $(\bar{x} - \sigma)$ and $(\bar{x} + \sigma)$, respectively, for low limitation and high limitation. The coefficient values beyond the limitations were removed from further investigation.

3.1.3. FFNN Implementation

Coefficient values in the limitation were fed into FFNN. Four coefficients (*cont*, *corr*, *ASM*, and *hom*) and the material surface were used respectively as input nodes and output nodes. Then the numbers of hidden nodes were set up as described previously. In addition, the learning algorithm chosen was Levenberg–Marquardt (trainlm) because it is faster and more efficient⁹⁾. To obtain the optimum network, a trial and error scheme was conducted by combining all those nodes (e.g. [i; h; o] for [input node; hidden node; output node]; example combination [4, 6, 1], [4, 10, 1],... or [4, 9, 1]) but only one combination that provided good performance was selected.

3.2. Results and Discussions

Figure 5 portrays the range of four coefficient values for the six material surfaces after limitation. Each coefficient

value showed a limitation. The limitation shows two bars at the top and below, represented as a high limitation (HL) and low limitation (LL). Limitations that are intermediate of the high and low limitations are medium limitations (ML). Observation reveals that all surfaces yielded different coefficient values except surfaces (b) and (c). Both showed approximately similar coefficient values for all coefficients. To overcome the redundancy of coefficient values during FFNN learning, both were combined to the same surface.

Results of analyses indicate that only 53.8% of 360 images of surfaces (surface (a) = 39 images, surface (b) = 50 images, surface (c) = 27 images, surface (d) = 26 images, surface (e) = 30 images, and surface (f) = 20 images) were used for FFNN as input nodes because of limitations. Before feeding into FFNN, a database of images of surface materials was divided into three subsets: 60% of the database for training; 20% of the database for validation, and 20% of the database for testing. No specific proportions for FFNN subsets were set. At this point, the proportions of subsets are chosen arbitrarily. Generally, the training subset should be larger than the validation subset and the testing subset.

In this study, the absorption coefficients (α) of six material surfaces are referred from reports of the relevant literature^{10,11)}. By identifying the material surfaces, we are able to ascertain the absorption coefficients of surfaces simultaneously. To identify the material surfaces, we used a classification number (1–5) to represent the output parameter: 1. Surface (a) ($\alpha = 0.07$), 2. Surface (b) and (c) ($\alpha = 0.02$), 3. Surface (d) ($\alpha = 0.04$), 4. Surface (e) ($\alpha = 0.4$) and 5. Surface (f) ($\alpha = 0.06$).

Results of analyses show that the optimum network [4, 6, 1] with $MSE \leq 0.0018$ and correlation coefficient $r \geq 0.9$ was obtained for both training and validation subsets. To confirm their performance, the testing subset (39 surface images) showed $MSE \leq 0.07$ with correlation coefficient $r \geq 0.9$. Subsystem 1 performance is inferred to be good at this stage.

The restrictions of Subsystem 1 are the following: 1. It can only identify the material surfaces depending on the database of material surfaces used. If more databases of material surfaces were used, then more material surfaces can be identified. 2. Generally, the real absorption coefficients of material surfaces in rooms depend on the material thickness, presence or absence of an air layer and absorptive layer, and so on. Then, it is difficult to obtain a real absorption coefficient only a surface form image. For practical usage, the author referred to related reports of the absorption coefficient.

4. Subsystem 2

4.1. Methodology of Subsystem 2 Development

4.1.1. DVP Implementation

The same camera for Subsystem 1 was used with focus lenses of 18–70 mm to capture two images at one view. The camera was set in autofocus mode. Figure 6 presents an example of predicting dimensions of objects in one image

Fig. 5. Limitation of coefficient values for six material surfaces

at one view. Lines connect corresponding points at objects. For example, to measure blackboard object dimensions, four corresponding points of A, B, C, and D must be obtained. Each corresponding point is connected to form lines: line 9, 10, 11, and 12. As described above, the survey-from-photo requires a standard scale. Therefore, the authors propose to use a ruler that is attached at an appropriate view as reference dimension in this "ruler method". A ruler is preferred because it is practical and simple to attach to the view region to be measured.

To investigate the repeatability of dimension prediction, 100 dimensions at several objects were examined. The predicted dimensions using DVP as Subsystem 2 were compared with measured dimensions obtained from laser measurements using a laser indicator (LS-501A; MAX Co., Ltd.). The *MSE* and correlation coefficient (*r*) are applied for assessments.

4.2. Results and Discussions

From analyses of Subsystem 2, the results are given in Fig. 7, which revealed a high correlation coefficient ($r \geq 0.99$) between predicted values using Subsystem 2 and measured values with $MSE \leq 0.009$. Results show that Subsystem 2 provided high reliability using no physical measurements.

5. Implementation in Actual Rooms

To investigate the identification capability of both subsystems, actual rooms of four types at Oita University were used. The rooms of four types were the following. 1. 130 m³ with 12 pieces of furniture (desk and chair); 2. 130 m³ with 8 pieces of furniture; 3. 260 m³ with no furniture; 4. 260 m³ with 12 pieces of furniture.

Subsequently, the results from both subsystems were used to simulate the RTs of rooms to confirm their reliability. The RTs of the rooms were computed using FEA. The resulting RTs were compared with RTs by FEA using actual absorption coefficients and dimensions obtained from reference to the literatures and laser measurements.

For Subsystem 1, 294 images of material surfaces were

Fig. 6. Identification dimensions using "ruler method".

obtained (surface (a) = 60 images, surface (b) = 53 images, surface (c) = 48 images, surface (d) = 63 images, surface (e) = 41 images, and surface (f) = 25 images). A limitation ($\bar{x} - \sigma$) and ($\bar{x} + \sigma$) at coefficient values for all images was calculated using the procedures described above. Surfaces consisting of coefficient values within the limit were used to feed into FFNN.

At Subsystem 2, the target objects were the room, door, window, and furniture. These objects were captured using a camera and fed into DVP to identify the dimensions.

The FEA in the time domain was used to obtain the room RTs. In the FEA, room dimensions and surface impedance of boundaries are necessary for mesh generation and the boundary conditions. For this study, these were obtained, respectively, from Subsystems 1 and 2. To obtain the RTs, the receiving points were set at certain locations in a room. Two rooms were set with 25 receiving points each. The other two were set with 27 receiving points each. The totals of receiving points of the four rooms were 104. Each receiving point donated impulse response. We filtered the impulse response with octave bandwidth of the center frequency 500 Hz using a tone burst signal. Then, the impulse response is useful to calculate the RTs at 500 Hz.

5.1. Results and Discussions

Based on the limitation, there are 61% from 294 images (surface (a) = 32 images, surface (b) = 35 images, surface (c) = 33 images, surface (d) = 31 images, surface (e) = 26 images and surface (f) = 23 images). Images of surface materials that consist of coefficient values within the limitation were fed into FFNN.

Figure 8 reveals that identification by Subsystem 1 yields a good correlation coefficient: $r \geq 0.90$. Unfortunately, identification on 3, which is Surface (d) ($\alpha = 0.04$) showed inconsistent results because 29% of 31 images were below the limit at the *ASM* training images database. The window is a transparent and light-reflecting material. In this case of a transparent window, it is difficult to capture consistent images of material surfaces because of its surface characteristics.

Fig. 7. Subsystem 2 dimensions and measured dimensions.

Fig. 8. Subsystem 1 and actual classification in actual rooms.

Fig. 9. Subsystem 2 dimensions and measured dimensions for actual rooms.

Fig. 10. RT_actual and RT_subsystem for actual rooms.

Figure 9 presents results of room dimensions. Following the capture procedure, the Subsystem 2 produces a high correlation coefficient $r \geq 0.99$ with $MSE \leq 0.200$ for identification of the dimensions.

RTs obtained by FEM using parameters obtained from subsystem (RT_subsystem) are compared with RTs by FEA using actual absorption coefficients and dimensions (RT_actual) in Fig. 10. This process yields practical results of RTs at 104 receiving points with correlation coefficient $r \geq 0.85$ and $MSE \leq 0.008$, which means that the RTs can be simulated well by FEA using both subsystems.

Results show that techniques of Subsystems 1 and 2 provide good identification capability to actual rooms and that both are also useful to simulate the RTs of rooms.

6. Conclusions

Aiming for practical applications, identification techniques of material surfaces and dimension using photographic were developed. Subsystem 1, using GLCM, was used to analyze the texture features of image of material surfaces. The Haralick coefficients were fed into FFNN to identify the surface material. Simultaneously, the absorption coefficient is obtainable. Subsystem 2, comprising DVP and the "ruler method", was used to identify the dimensions. Results show good identification reliability with correlation coefficient $r \geq 0.90$ from both subsystems. A basic concept to identify surface material and dimensions using four Haralick coefficients and "ruler method" yielded practical results. With some improvements, such as adding more Haralick coefficients, the method will

be more accurate and effective when used for practical applications. Furthermore, it is useful for simulating sound fields of rooms.

References

- 1) Min, D.L., Kang, T.T. and Bo, S.S.: Estimating the Sound Absorption Coefficient of Perforated Wooden Panels Using Artificial Neural Networks, *Applied Acoustics*, Vol. 70, pp. 31–40, 2009
- 2) Hodgson, M. and Scherebnyj, K.: Estimation of the Absorption Coefficients of the Surfaces of Classrooms, *Applied Acoustics*, Vol. 67, pp. 936–944, 2006
- 3) Honeycutt, C.E. and Plotnick, R.: Image Analysis Techniques and Gray-Level Co-occurrence Matrices (GLCM) for Calculating Bioturbation Indices and Characterizing Biogenic Sedimentary Structures, *Computers & Geosciences*, Vol. 34, pp. 1461–1472, 2008
- 4) Haralick, R.M., Shanmugam, K. and Disstein, I.: Textural Features for Image Classification, *IEEE Transaction System, Man and Cybernetics*, Vol. 3, pp. 610–621, 1973
- 5) Survey-from-photo taken from "www3.plala.or.jp/SolidFromPhoto/"
- 6) Spa, C., Garriga, A. and Escolano, J.: Impedance Boundary Conditions for Pseudo-spectral Time-domain Methods in Room Acoustics, *Applied Acoustics*, Vol. 71, pp. 02–410, 2010
- 7) Okuzono, T. et al.: Accuracy and Efficiency of Time Domain Finite Element Method for Sound Field Analysis of Room, *Proceedings of Inter-Noise-2009*. On CD ROM 2009
- 8) Okuzono, T. et al.: Fundamental Accuracy of Time Domain Finite Element Method for Sound Field Analysis of Rooms, *Applied Acoustics*, Vol. 71, pp. 940–946, 2010
- 9) Hagan, M.T. and Menhaj, M.: Training Feed Forward with the Marquardt Algorithm, *IEEE Transactions Neural Networks*, Vol. 5, pp. 989–993, 1997
- 10) Maekawa, Z. and Lord, P.: *Environmental and Architectural Acoustics*, E & FN Spon, 1993
- 11) Urano, Y. and Nakamura, H.: *Architecture Environmental Engineering*, Moriko Co., 1996 (in Japanese)

[2011年6月20日原稿受理 2011年10月14日採用決定]