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RESEARCH ARTICLE

Automatic Parametric Modeling Technique for Structural Design Standardization

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ABSTRACT The challenge in designing new three-dimensional (3D) shapes is that considerable manual effort is required for repeated designing and verification to satisfy the required specifications. Extracting and standardizing parametric design rules from a designed 3D shape dataset will be useful for drastically reducing the design time. This paper describes a framework of automatically generating parametric models, design rules, in order to standardize designs for structural systems. In this framework, a design dataset whose dimensions and shapes have parametric relationships with a target shape is extracted using a new retrieval method. This method is an improvement of a conventional similar shape retrieval method. After the extraction of the design dataset, the corresponding parts between the collected shapes are automatically identified and parametric models are automatically generated. This new similar shape retrieval method has two improvements over the conventional method that uses images of 3D shapes captured from multiple directions. First, 3D shapes are converted to unit shapes by stretching or shrinking along each axis. Second, similar shapes are extracted using a special artificial intelligence (AI) model that learns parametric relationships. The effectiveness of the proposed framework is evaluated using the 3D shape data of various structural shapes. Although the accuracy rate of similar-shape retrieval based on parametric relationships was 62% in the conventional method, by using unit shapes and special AIs, it was improved to 99% in the new method. Moreover, the corresponding parts between similar shapes were automatically identified, and parametric models were automatically generated. The effectiveness of this framework has been demonstrated.

INDEX TERMS Automatic design, image recognition AI, parametric model, similar shape retrieval, standardization, unit shape.

I. INTRODUCTION

The design of three-dimensional (3D) shapes requires significant manual effort for design and validation to satisfy the required specifications. Therefore, the standardization and automation of specific aspects of the design will be helpful in reducing the design time. Parametric models that can express the relationships between shapes and dimensions are required to standardize design objects. Parametric models are relational expressions where dimensions of a design object change corresponding to the change in one dimension. In the design using a parametric model, the dimensions can be automatically set based on the relational expressions. Therefore, it is meaningful in design automation to standardize and manage design objects using parametric models. However, parametric modeling is not easy because it is generally based on human knowledge and experience.

Previous research on automated design comprised studies on optimizing the design parameters of parametric models using numerical simulations such as structural analysis and computational fluid dynamics (CFD). For example, in [1]–[3], a parametric model is used as a model of numerical simulation. Design parameters are determined via optimization calculation and then substituted into the parametric model for an automatic design. In [4] and [5], the past design data were reused for optimization. CAD models with parametric relationships and finite element method (FEM) simulation models are linked and designed automatically using the FEM analysis results. Reference [6] reports a platform for designers to set parametric relationships between multiple

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parts in an assembly. These approaches assumed that in all cases, parametric models can be built by designers themselves or that the parametric models are known and configurable. However, a designer may not necessarily understand the parametric models for a specific design shape or be able to construct them.

This study proposes a framework for automatically designing parametric models through retrievals based on parametric relationships to a target shape (hereafter, referred to as target) for similar parametric 3D shapes (hereafter, referred to as similar parametric shapes). The retrievals are made from a set of data of designed 3D shapes (hereafter, past 3D shapes) in a design database (hereafter, database). This framework is called the parametric modeling technique whose purpose is to automatically construct parametric models that express sets of similar parametric shapes. The database contains several 3D shapes, including the design know-how. Therefore, parametric models constructed using similar parametric shapes that are extracted from them contain plenty of the design know-how. Parametric models enable novice designers to utilize their design know-how to achieve high-quality designs. The shapes in the database are managed by the standard parts and assemblies associated with parametric models. For a novel design, relevant dimensions are automatically set when the appropriate parametric model is selected, and its parameters are adjusted accordingly. Thus, parametric models using this framework enable automatic design.

This framework requires similar parametric shape retrieval and automatic parametric modeling techniques. Several studies are based on similar shape retrieval methods [7]–[20]. However, it is difficult to retrieve similar parametric shapes using the existing similar-shape retrieval methods because the relationships between dimensions are not considered in the existing works. A few similar parametric shape retrieval methods have been reported previously. For example, in [21], sketch-based parametric part retrieval method by view dependent graphs is proposed, and in [22], a parametric shape set nearest to a target is retrieved using descriptor space representation. However, these methods cannot be applied to the proposed method. Next, to our knowledge, this is the first time that a parametric model is constructed automatically using past data. Therefore, we propose a framework based on two techniques. Technique 1 involves retrieving a design dataset of similar parametric shapes from a database based on parametric relationships. Technique 2 involves automatically developing parametric models that express the design parameters (dimensions) and shapes from the extracted 3D shapes. The proposed framework was validated using a database with various parametric shapes, and its effectiveness is shown.

The main contributions of this paper are as follows: (i) the proposal of a framework for automatically constructing parametric models for an automated design and its standardization, and (ii) the development of the techniques for a similar parametric shape retrieval and an automatic parametric model generation. Elaborate technologies for this framework, including the conversion into new shapes, special AIs, identification of corresponding parts, and generation of models via a statistical method, were developed.

This paper is organized as follows. Section II discusses the related work. Section III explains parametric modeling problems. Section IV proposes a framework for constructing parametric models. Section V describes the demonstration of the framework. Section VI discusses the results obtained by applying the proposed framework to the problem. Section VII presents the conclusions.

II. RELATED WORK

In [1]–[6], an automatic design method using past design data and parametric models is presented. In [1], the authors designed the outline of an aircraft parametrically based on hydrodynamics using computer aided design (CAD) and optimized its design parameters via the Gaussian regression model using the data of the previous design. The CAD model design was automatically completed using these parameters. Reference [2] reported a method developed by automatically designing the size, number, and arrangement of ejector pins within a die used in injection molding. In this method, an appropriate solution was derived using a genetic algorithm. The cooling performance and product quality were considered, and a parametric CAD model was employed. Reference [3] reported an automatic design method for fabricating aquatic robots based on multidomain optimization accounting for resistance and maneuverability. In [4], past data were used as the initial values of parameters in optimization calculations through knowledge objectification. In [5], a method was devised for satisfying design constraints by optimizing the integration of an existing component module from a past knowledge base and by using new design components to make adjustments. In [6], the authors developed a platform setting the parametric relationships for dimensions and features among multiple parts comprising an assembly, replacing the parts in a library and changing shapes on demand. In these studies, the parametric relationships were derived from mathematical formulas and previous experience and were used for design through optimization. However, these studies did not focus on the construction of parametric models.

In addition, studies were conducted on content-based methods to search for 3D shapes similar to targets, using 3D model properties to search for similar models [7]–[10]. In [7], a feature-based similarity search method using high-dimensional feature vectors was proposed. In [8], the authors developed a method using a model dependency graph. Reference [9] presented a method converting the CAD data to a graphbased data. In [10], the authors converted 3D shapes to point clusters and later used features to express the distances and orientations as 2D histograms. Reference [11] reported a method to express 3D shapes with voxels, i.e., objects with a small volume. In [12]–[15], 3D shapes were expressed in multiple resolutions and their feature information was used. References [16]–[19] reported the use of the features of 2D images obtained by photographing 3D shapes from multiple directions. In [20], the authors expressed 3D shapes using the principal plane analysis and dynamic planning methods. These methods retrieve shapes similar to targets using various measures such as the distance of features among the shapes, histograms, and probabilistic graph models. It is possible to search for shapes, with similar appearances, despite different relationships between the shape size and the detailed parts. However, as elaborately described in Section III, due to low the similarities among the 3D shapes with parametric relationships, it is difficult to extract similar parametric shapes using only the similarity of the conventional method. Therefore, our study aimed to address the same, and we found that similar parametric shapes could be retrieved based on parametric relationships by using unit shapes maintaining the axial shape features in each axial direction and using AI that could learn the parametric relationships even during low similarities among the shapes.

In [21] and [22], similar parametric shape retrievals are proposed. Reference [21] presents a sketch-based parametric part retrieval method using VD graphs composed of feature vertices and edges. This method enables the sketch-based retrieval using the feature points and lines of the silhouettes of 3D shapes. However, it is not suitable for automatic parametric modeling because the ratio among the dimensions is not considered. In [22], the target and each parametric shape set are expressed by a point and a manifold in a feature space, respectively, using a descriptor space representation; a parametric model is retrieved using the distance between a point and manifolds. This method utilizes a set of classified parametric models for retrieval.

Finally, in [23] and [24], the methods for matching the orientation of extracted 3D shapes are described. Reference [23] presented a method for identifying the phases between shapes using the shape features via principal component analyses. In [24], the shapes were polygonized and the phases were identified using normal lines. These methods were effective for similar shapes with similar external features; however, using these methods, it was difficult to identify the corresponding parts of similar parametric shapes with different external features. Our proposed method is characterized by identifying the corresponding parts among similar parametric shapes by matching the shape directions using the unit shapes of similar parametric shapes and identifying the similar parts.

III. PROBLEM SETTING

As a prerequisite, various past 3D shape data are stored in the database. As shown in Fig. 1, a set of parametric shapes similar to the target is sought from among the various 3D shapes in the database, and then a parametric model is automatically developed.

This section describes the problems in extracting shapes having the same parametric relationships with the target as the group of shapes used in the conventional similar-shape retrieval method. Herein, we consider L-shaped 3D shapes with parametric relationships as shown in Fig. 2. In the figures, the red and black numbers are the dimensions.

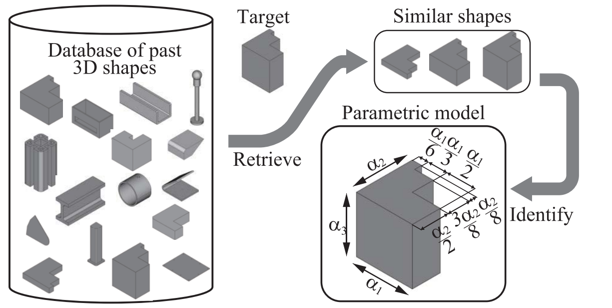

FIGURE 1. Conceptual diagram for identifying a parametric model of a target shape from various past three-dimensional (3D) shapes available in a database. Similar shapes to the target are extracted from a database of past 3D shapes and their parametric model is identified.

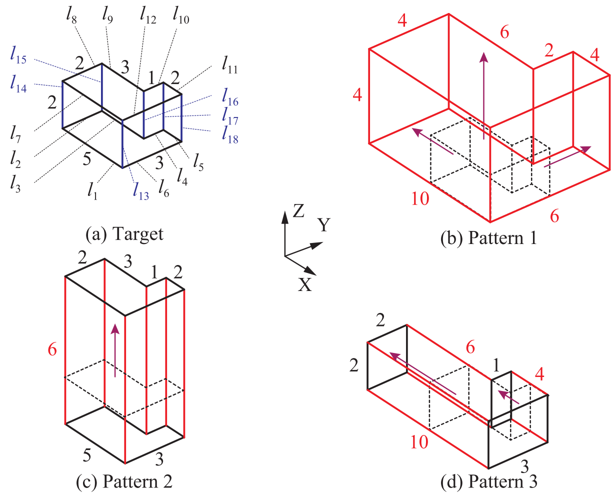

FIGURE 2. Examples of 3D shape patterns classified in the same group. The shape in (a) is the target, the shapes in (b)-(d) have the same parametric relationships as the targets.

Fig. 2(a) is the target. Pattern 1 is a shape similar to the target (all the dimensions in Fig. 2(b) have a similarity ratio of 2 to the target (Fig. 2(a)). Pattern 2 is a 3D shape created by sweeping a two-dimensional (2D) shape in a direction perpendicular to it (a 3D shape, such as pillar-like parts). Pattern 3 is a shape created by extending the target while maintaining the ratio of the length of each edge in each axial direction.

In existing studies on similar-shape retrievals [25], the similarities between the targets and all 3D shapes in a database are calculated using the features of 2D images of 3D shapes captured from multiple directions; thereafter, the 3D shapes are detected in the descending order of similarity. The details of previous studies on similar-shape retrievals will be described in Sections II and IV-A. The 2D images of the 3D shapes shown in Fig. 2 as used in the conventional similar-shape retrieval method are shown in Fig. 3. Fig. 3(i) shows a reference view image, and Fig. 3(ii) shows the image when the 3D shape in Fig. 3(i) is rotated 45° around the X axis. For every 2D image, the scale is adjusted such that the 3D shapes are largest within a range that fits the image size.

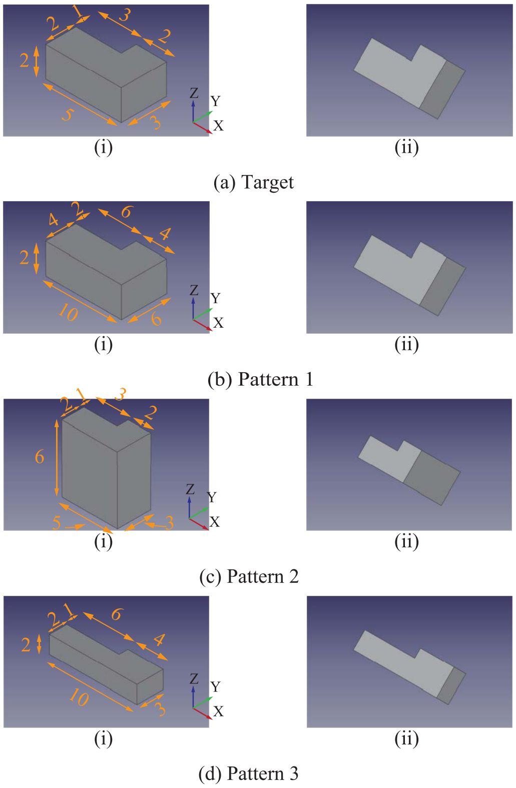

FIGURE 3. **Examples of 2D images of the target and patterns 1-3 used in similar shape retrieval. The shape in (a) is the target, and the shapes in (b)-(d) are patterns 1-3. The view shown in (i) is a reference view of the 3D shape, and the view shown in (ii) is a view in which the 3D shape shown in (i) is rotated 45° around the X axis.**

When the shapes shown in Fig. 3 are classified by a conventional similar-shape retrieval method, as shown in Figs. 3(a) and 3(b), the 2D images used for the target and pattern 1 are the same, and therefore, these shapes can be classified as belonging to the same group. On the other hand, as shown in Figs. 3(c) and 3(d), the images for patterns 2 and 3 differ significantly from the target images. Hence, they cannot be classified as similar shapes. Therefore, the purpose of this study is to develop a method for classifying the target and patterns 1–3 into the same group and generating parametric models from the 3D shapes in this group.

IV. DESIGN OF THE PROPOSED FRAMEWORK

In this section, we explain similar-shape retrieval based on the features of 2D images, which are the photographs of 3D shapes from multiple directions. This is the conventional method. Thereafter, we propose a framework combining two techniques for parametric modeling.

A. SIMILAR-SHAPE RETRIEVAL

The existing similar-shape retrieval method used in this study proceeds as follows. First, for all 3D shapes in the database, 2D images are captured from all directions. The multiview images (hereafter, MVIs) for each 3D shape are acquired and stored in the database. Next, an artificial intelligence (AI) model is constructed using the MVIs and 3D shape labels.

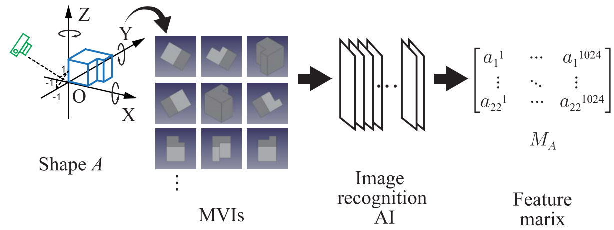

FIGURE 4. **Feature calculation for 3D shapes using AI. Using image recognition AI, the feature matrix M_A of the shape A is calculated from the MVIs composed of images captured from multiple directions.**

The features of the 3D shapes are calculated using this AI. Next, the similarity between the features of the targets and 3D shape in the database is calculated. Finally, the output is arranged in the order of the highest to the lowest similarity. The features of the 3D shapes are identified by creating MVIs composed of images captured from multiple directions for each shape, as shown in Fig. 4, and then calculating 1024 feature vectors per image using the AI. In this study, the images of a shape are captured from 22 directions by the following procedure. First, a 3D shape is placed on the XY plane, and a 2D image is obtained, so that the 3D shape fits in the 2D image frame from the direction of the normal vector of the plane passing through $(x, y, z) = (-1, 0, 0), (0, -1, 0), (0, 0, 1)$. Next, a 3D shape is captured at every 45° of rotation around the X axis, and the images are obtained from eight directions. Thereafter, by repeating the same operation around the Y and Z axes, images are obtained from a total of 24 directions. Finally, 22 images are obtained, considering that the images overlap when the shape is not rotated on each axis. These 22 images include the three pairs of images in which the positional relationship between the camera and the 3D shape is the same when the image is rotated 120°. However, their features of the images differed because of the different shading of each surface of the 3D shape. Therefore, a total of 22 images are used.

A list of 22 feature vectors is created for each shape. This list is called the feature matrix. The feature matrix of shape A is denoted by M_A, as in Fig. 4, and the feature vectors of the qth image of shape A are denoted by $\boldsymbol{a}_q$; the feature vectors of the rth image of comparative shape B is denoted by $\boldsymbol{b}_r$. The similarity S_{qr} between the feature vectors of $\boldsymbol{a}_q$ and $\boldsymbol{b}_r$ is defined using the cosine similarity as follows:

$$S_{qr} = S(\boldsymbol{a}_q, \boldsymbol{b}_r) = \frac{\boldsymbol{a}_q \cdot \boldsymbol{b}_r}{|\boldsymbol{a}_q||\boldsymbol{b}_r|}. \tag{1}$$

The higher the S_{qr}, the more similar are their images. Determining the similarity between two shapes involves specifying the image of shape B having the highest similarity to the qth image of shape A, performing this specifying operation on all images of shape A, calculating the mean of the similarities of the 22 images, and calculating the similarity $S_{\mathrm{A}\rightarrow\mathrm{B}}$ between shapes A and B. $S_{\mathrm{A}\rightarrow\mathrm{B}}$ can be written as follows:

$$S_{\mathrm{A}\rightarrow\mathrm{B}} = \left(\sum_{q=1}^{22} \max_r S_{qr}\right) /22. \tag{2}$$

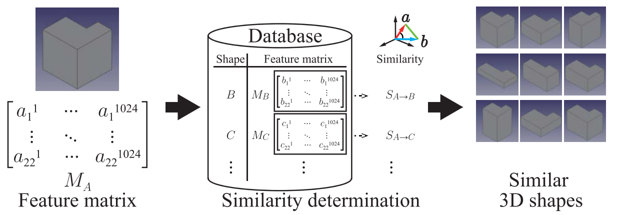

FIGURE 5. **Similar shape retrieval using features of shapes in database. The similarity is calculated using the feature matrix of shape *A* and the feature matrix of each shape in the database, and the similar shapes are extracted.**

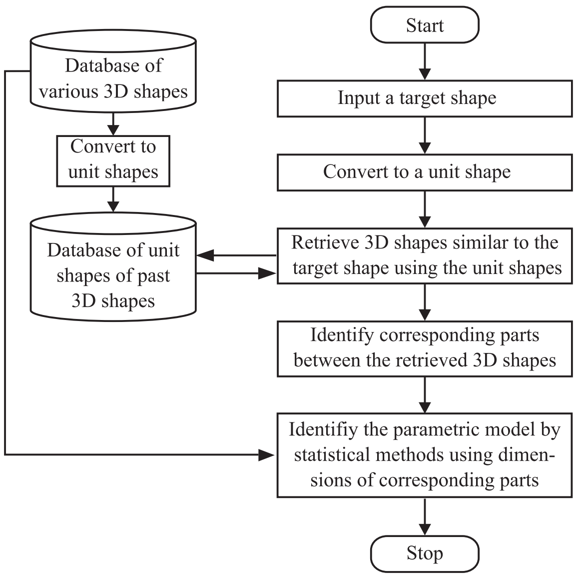

FIGURE 6. **Flow of the proposed framework for parametric modeling. A target shape and past 3D shapes in a database are each converted to unit shapes. Shapes having parametric relationships similar to a target are extracted based on similarity between unit shapes. The corresponding parts are identified between the retrieved 3D shapes, and the parametric model is identified by statistical methods.**

As shown in Fig. 5, the similarity between the target and all 3D shapes in a database is calculated. Thereafter, the 3D shapes with similarity greater than or equal to a set threshold are extracted in the order of the highest to the lowest shape similarity, and a similar shape set is output.

B. CONSTRUCTION OF A PARAMETRIC MODEL BY THE PROPOSED FRAMEWORK

The proposed framework is outlined and the following techniques constituting the framework are described.

- Technique 1: Retrieve similar shapes based on parametric relationships.
- Technique 2: Identify corresponding parts and generate parametric models.

1) OUTLINE OF THE PROPOSED FRAMEWORK

Fig. 6 shows the proposed parametric modeling framework. First, the target and all 3D shapes in the database for constructing a parametric model are each converted to unit shapes by transformation through normalization in each axial

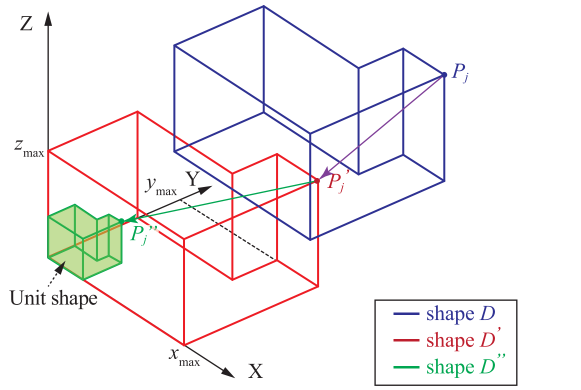

FIGURE 7. **Example of converting an original shape to a unit shape. Shape *D* is moved to shape *D*′ to align the origin position, and shape *D*′ is converted to a unit shape *D*″ by axial normalization.**

direction. Next, the similarity based on parametric relationships (SPRs) between the unit shapes of the targets and each 3D shape in the database are calculated. The 3D shapes with SPR values greater than the set threshold are extracted to create a set of similar parametric shapes. Finally, the parametric model is identified by statistical methods from each dimensional information of a set of similar parametric shapes. If no shape similar to the target is retrieved, the target and its unit shape are registered in a database. When shapes similar to the target are accumulated in the database, a parametric model can be constructed by the flow shown in Fig. 6.

2) TECHNIQUE 1

To find the parametric relationships between axial dimensions, each 3D shape in the database is converted to unit shapes for preprocessing. Next, the AI for recognizing shapes based on parametric relationships is developed, and shape retrieval based on parametric relationships is performed by calculating the feature matrices of each unit shape using the AI.

Fig. 7 shows the conversion of a shape D to a unit shape D''. The method is explained using the vertex $P_j(x_j, y_j, z_j)$ of shape D in the figure. Here, j indicates the index of the vertices of shape D. First, shape D is moved to shape D' to align the position of its origin. The minimum value for each axial component is extracted from the coordinates of all vertices of shape D. The coordinates of vertex $P_j'(x_j', y_j', z_j')$ are calculated as follows:

$$x_j' = x_j - \min_k x_k, \tag{3}$$

$$y_j' = y_j - \min_k y_k, \tag{4}$$

$$z_j' = z_j - \min_k z_k. \tag{5}$$

Next, the components of the respective coordinates of vertex P_j' of shape D' are divided by the maximum value in each axial direction of the component of the coordinates of all vertices of shape D' and assumed as vertex $P_j''(x_j'', y_j'', z_j'')$. The coordinates of vertex P_j'' are calculated as follows:

$$x_j'' = x_j' / \max_k x_k', \tag{6}$$

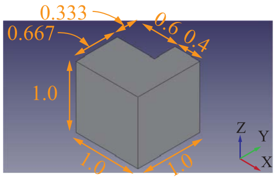

FIGURE 8. Unit shape of patterns 2 and 3. The shapes of patterns 2 and 3 are converted into the same unit shape.

$$y_j'' = y_j' / \max_k y_k', \tag{7}$$

$$z_j'' = z_j' / \max_k z_k'. \tag{8}$$

The unit shape D'' is created by axial normalization as described above. All the 3D shapes in the database are converted to unit shapes, and each unit shape and pre-converted shape are associated and stored in the database. By this conversion method, patterns 2 and 3 in Fig. 3 are converted into the same unit shape as that shown in Fig. 8. Therefore, both patterns can be classified into the same group.

Now, we describe the AI development for similar-shape retrieval based on parametric relationships. A 22-layer deep convolutional neural network with the same configuration as the AI used in the existing similar shape retrieval was used. This AI was called GoogLeNet (multi-layer coupled network) and it won the image classification challenge contest ISLVRC -2014 in 2014 [26]. A dataset of 3D shapes with linear parametric relationships was prepared as the training data. The training dataset contained 16 types of shapes, each with 100 shapes. The shapes of each type have parametric relationships classified into four patterns as described in Section III. Thereafter, using the MVIs of each 3D shape and 3D shape labels, the parametric datasets of the same type were learned by attaching the same labels. Thus, an AI for similar-shape retrieval that can output parametric relationships as features was developed. The AI is called PR-AI. The SPR between shapes was evaluated using the feature of each shape as calculated via PR-AI. Fig. 9 shows an example of a 3D shape dataset with parametric relationships used for training. In addition, to extract 3D shapes with higher SPRs, an AI for similar-shape retrieval based on parametric relationships using unit shapes was developed. In this AI, the training data 3D shapes shown in Fig. 9 were converted into unit shapes, and then, parametric relationships were learned using these unit shapes. This AI is called PRU-AI. PR-AI and PRU-AI use not only the 3D shape datasets with parametric relationships but also the datasets of regular parts as training data. Hereafter, the conventional AI for similar-shape retrieval based on shape similarity is called SS-AI and the AI that performs classification based on shape similarity using unit shapes is called SSU-AI. SS-AI and SSU-AI also use data sets of regular parts as training data.

The developed PR-AI and PRU-AI can be used to calculate the respective SPRs between the targets and all shapes in the database. Thereafter, the parametric shapes similar to the targets are extracted from the database in the order of higher SPR to lower SPR. The set of the extracted unit shapes is defined

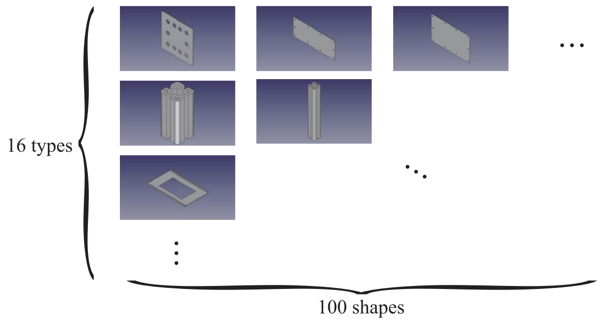

FIGURE 9. Example of a 3D shape dataset with parametric relationships for AI development. The dataset contained 16 types of shapes, each with 100 shapes.

as G_{unit}, and the set of the 3D shapes before conversion to the unit shapes associated with G_{unit} is defined as G_{ori}. In case of no shape with similarity or SPR greater than or equal to the threshold, no similar parametric shape is considered to exist in the database.

3) TECHNIQUE 2

To generate parametric models automatically, the corresponding parts, such as edges and vertices, between the 3D shapes within the set G_{ori} are automatically identified. Thereafter, the parametric models are constructed by a statistical method using the dimensions of each part as variables.

It is difficult to automatically identify the corresponding parts between 3D shapes in G_{ori} because the shapes may have different 2D image features (for example, the shapes in Figs. 3(c) and 3(d)) or they may have different orientations. Therefore, the unit shapes in G_{unit} are focused on the fact that they are similar and possess the axial-wise features of the 3D shapes in G_{ori}. Fig. 10 shows the procedure for identifying the corresponding parts between shapes. In step 1, target shape D_{trg} and similar shape D_{obj} are converted to unit shapes U_{trg} and U_{obj}, respectively. In step 2, U_{obj} is rotated to align U_{trg} with U_{obj}. The rotated U_{obj} is called $U_{\mathrm{obj}}{}^*$. In steps 3 and 4, the corresponding edges and vertices of U_{trg} and $U_{\mathrm{obj}}{}^*$ are identified. Finally, in step 5, the corresponding parts of D_{trg} and D_{obj} are specified based on the alignment information in step 2 and the corresponding parts information in steps 3 and 4. Thus, it becomes possible to identify the corresponding parts of D_{trg} and D_{obj} automatically. The detailed procedure is as follows. Fig. 11 shows the method for creating the feature matrices to orient the shapes. First, to identify the orientation of a prescribed shape D, the feature for each shape orientation is defined. Specifically, 24 (= 4 × 6) images are prepared by imposing a rotation of 90° on each image of unit shape U_D of shape D captured from six positive and negative directions relative to each axis and then using SS-AI to calculate the feature vector $\boldsymbol{d}_{Dst}$ of each image. Here, s indicates the direction in which the U_{D} is captured and is 1, 2, …, 6. Further, t indicates the number of times the captured image is rotated by 90° and is 0, 1, 2, or 3. Next, as shown in Fig. 11, each image is arranged as a cube based on the direction wherein it was clicked, and

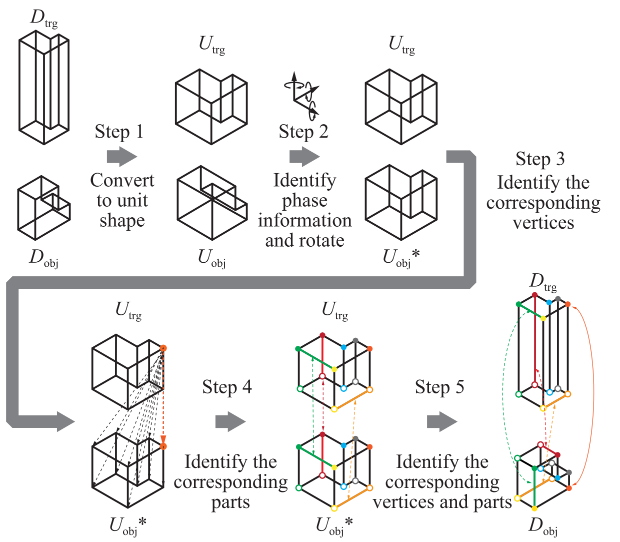

FIGURE 10. Procedure to identify corresponding parts between shapes with their unit shapes. In step 1, D_{trg} and D_{obj} are converted into unit shapes U_{trg} and U_{obj}. In step 2, the phase information of both is identified, and the direction is aligned. In steps 3 and 4, corresponding edges and vertices are identified. In step 5, corresponding parts of D_{trg} and D_{obj} are identified from the obtained information.

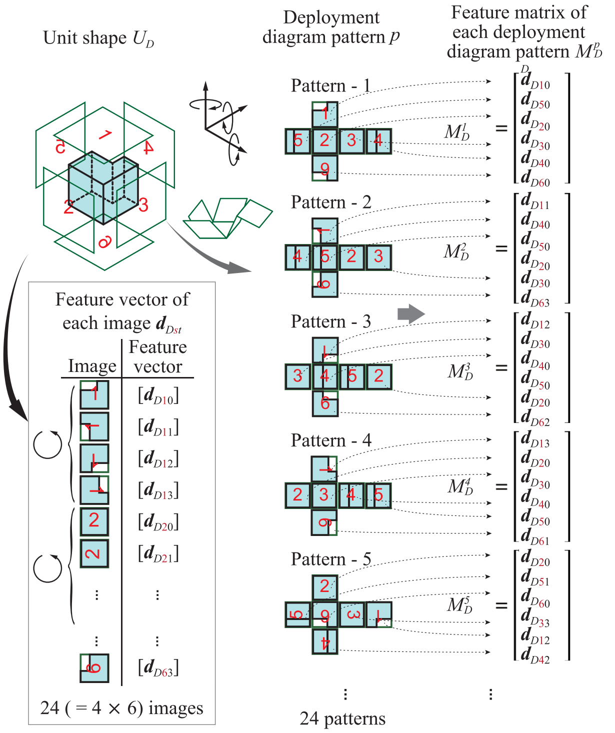

FIGURE 11. Method for creating feature matrices of deployment diagrams used for the orientation of shapes. 24 images are prepared by imposing a rotation of 90° on each image of unit shape U_D of shape D captured from six positive and negative directions relative to each axis. Then, each feature vector d_{Dst} is calculated. Each image is arranged in a cube shape, six faces are numbered, and 24 deployment diagrams are created. The feature matrix M_D^P of a development diagram is defined by arranging the feature vectors d_{Dst} of the image in an array.

the six faces are numbered; a deployment diagram is created from this pseudo cube. As shown in this figure, a deployment diagram is created by setting one side of the cube on the top face. Each time the cube is rotated 90° about the center of the top face, a deployment diagram is created, and the same operation is repeated for all six faces to create 24 deployment diagrams. Thereafter, the feature matrix M_D^p of a development diagram is defined by arranging the feature vectors $\boldsymbol{d}_{Dst}$ of the image in an array as shown in Fig. 11. In Fig. 11, p is the index of the pattern number of deployment diagrams.

Next, the similarity between U_{trg} and U_{obj} deployment diagrams is calculated. The deployment diagram with the highest similarity is selected, and the phase for aligning shape orientations is identified. The similarity of the features in the deployment diagrams is defined by calculating the similarity of all six faces of the feature $M_{\text{trg}}^{p_t}$ in the U_{trg} development diagram and the feature $M_{\text{obj}}^{p_o}$ in the U_{obj} deployment diagram. Here, p_t is the index of the pattern number of the deployment diagrams of U_{trg}, and it takes the values $1, 2, \ldots, 24$. And p_o is the index of the pattern number of the deployment diagrams of U_{obj} and is $1, 2, \ldots, 24$. Thus, the total similarity $T_S(p_t, p_o)$ of all six faces is calculated

$$T_S(p_t, p_o) = \sum_{w=1}^{6} S(M_{\text{trg}}^{p_t}[w], M_{\text{obj}}^{p_o}[w]). \tag{9}$$

Here, w is the row number of the feature matrix and takes the values 1, 2, ..., 6. Thereafter, $M_{\text{trg}}^{p_t}[w]$ is the wth row component of feature matrix $M_{\text{trg}}^{p_t}$ in the deployment diagram pattern p_t of U_{trg}, and $M_{\text{obj}}^{p_o}[w]$ is the wth row component of the feature matrix $M_{\text{obj}}^{p_o}$ in the deployment diagram pattern p_o of U_{obj}.

The phase for aligning the orientations of U_{trg} and U_{obj} is identified using the deployment diagram patterns p_t and p_o when T_S is the maximum. Using the obtained phase information, $U_{\text{obj}}{}^*$ is obtained by rotating U_{obj}, and the set obtained by aligning the phases of the shapes in G_{unit} is defined as $G_{\text{unit}}{}^*$.

Next, the corresponding parts between U_{trg} and U_{obj} in $G_{\text{unit}}{}^*$ are identified from information such as their vertex coordinates, and the corresponding parts between D_{trg} and D_{obj} within G_{ori} are identified using the information for the conversion to unit shapes and the phase information for the alignment of shapes in G_{unit}.

Thereafter, the information on the straight and curved parts is extracted from the CAD data of each shape, a size table summarizing the dimensional information is prepared for each corresponding part, and a parametric model is constructed by a statistical method using each dimension as a variable. In this paper, the straight parts are focused as an initial examination for constructing parametric models. The information on the straight parts used for the model construction contains the coordinates of both ends of the straight lines and their lengths. First, as shown in Fig. 12, the dimensions of each part of the shapes in the set G_{ori} are summarized in the size table. For no corresponding part among the shapes, the dimension is not described in Fig. 12 and is not treated as a

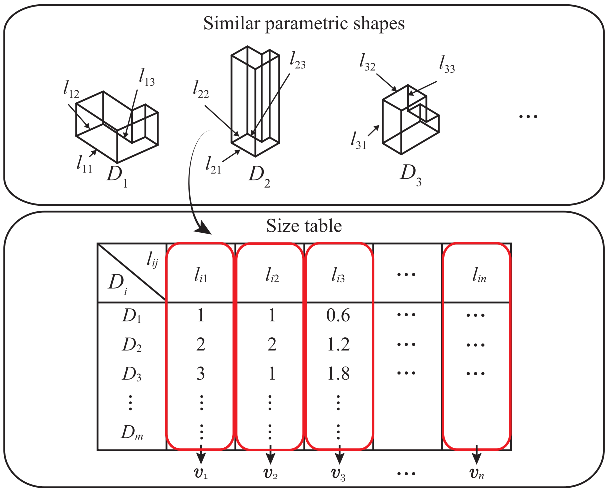

FIGURE 12. Creating a size table with similar parametric shapes and defining dimension variables. The sizes of the corresponding edges of similar shapes are tabulated and the columns of each edge are defined as dimension variables.

dimension variable. Here, the dimension of each part of the ith shape D_i in G_{ori} is defined as l_{ij}. The total number of shapes in G_{ori} is m, and the total number of parts with dimensions of each shape D_i is n. The jth column dimension variable in the size table in Fig. 12 is defined as $\boldsymbol{v}_j = [l_{1j}, l_{2j}, \ldots, l_{mj}]$, and the set of dimension variables V is defined as $V = [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_n]$. Next, a parametric model expressing the relationships between dimensions is developed using the set of dimension variables V. The variables with variance greater than a threshold are extracted from the set of dimension variables V as an objective variable group Ψ. A variable ψ_i, which is the ith element of the variable group Ψ, is set as the objective variable, all the variables other than the variable ψ_i in the variable set V are set as the candidate variable group Γ_i of the explanatory variables, and the data set (ψ_i, Γ_i) is set. To select the explanatory variables with a high contribution to the objective variable ψ_i, the explanatory variables $\widetilde{\gamma_i}$ with high contributions from the dataset (ψ_i, Γ_i) are selected in a stepwise method. A parametric model is constructed using an objective variable ψ_i and the selected explanatory variables $\widetilde{\gamma_i}$. The hth selected explanatory variable is defined as $\widetilde{\gamma_{ih}}$.

In our work, multiple regression analysis (MRA) was used as the statistical method for modeling. In MRA, the objective variable ψ_i is calculated by

$$\psi_i = \beta_0 + \sum_{h=1}^{k} \beta_h \cdot \widetilde{\gamma_{ih}}. \tag{10}$$

Here, k is the total number of selected explanatory variables. The least squares method is used to calculate the regression parameters $\beta_0, \beta_1, \ldots, \beta_k$. A parametric model is constructed with each dimension variable belonging to the group Ψ as a target variable in order. Linear models with a coefficient of determination below 0.95 are excluded. To obtain the relationships between the dimensions corresponding of each shape, a parametric model is developed using MRA to express the relationships between the dimensions of the target using a relatively simple model. In addition, nonlinear models are constructed after linear models, however nonlinear parametric modeling is not performed in this study.

V. DEMONSTRATION OF THE PROPOSED METHOD

In this section, the two techniques of the proposed framework are demonstrated using 3D shapes with parametric relationships.

A. EXPERIMENTAL SETTINGS

1) EXPERIMENTAL SETTINGS FOR TECHNIQUE 1

The following four methods were examined based on the combination of "classification based on parametric relationships or conventional classification" and "whether converting to unit shape or not." In the SS-method, SS-AI is used and the shapes are classified based on their shape similarities. This is the conventional method. In the SSU-method, the shapes are classified based on their shape similarities as determined by SSU-AI using their unit shapes. In the PR-method, PR-AI is used and the shapes are classified based on their SPRs; in the PRU-method, the shapes are classified based on their SPRs by PRU-AI using their unit shapes. For the database, a total of 2000 3D shapes were prepared. As shown in Fig. 9, there were 16 types that had parametric relationships with 100 shapes of each type, and 400 shapes for regular design parts. Here, structural parts designed for electronics are utilized as regular design parts. In all, 80% of the data volume per type was used to learn the parametric relationships, and the remaining 20% was used as targets for the crossover verification of all shapes within the database. Four methods were evaluated for the number of types that could be classified without mixing with other types of shapes and the accuracy rate. The accuracy rate R of each method was calculated via the following procedure. First, the accuracy rate R_{typ_i} of the ith parametric shape type is calculated as

$$R_{\mathrm{typ}_i} = \frac{1}{20} \sum_{j}^{20} R_{ij}. \tag{11}$$

Here, variable R_{ij} is the accuracy rate of the jth target shape of the ith parametric shape type. Next, the accuracy rate R of each method is calculated using the accuracy rate R_{typ_i} as

$$R = \frac{1}{16} \sum_{i}^{16} R_{\mathrm{typ}_i}. \tag{12}$$

Thereafter, the number of types that could be classified without mixing with other types of shapes was defined by investigating the occurrence of other shapes in the set of similar extracted parametric shapes.

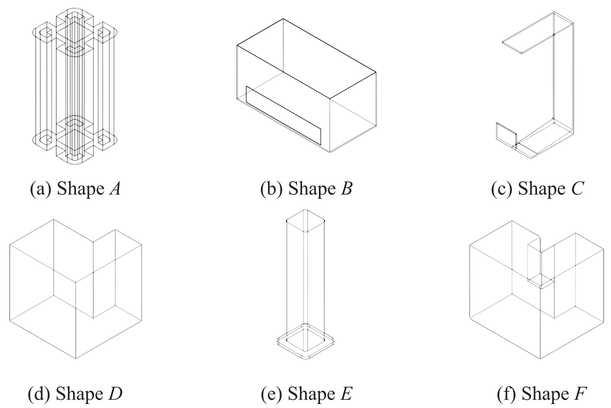

FIGURE 13. Examples of targets for parametric models. Parametric models are constructed for the shapes $A - F$ using techniques 1 and 2.

TABLE 1. Classification results of the conventional and proposed methods.

Method	Accuracy rate	Number of types that could be classified without mixing other shapes
SS-method (conventional method)	62.54%	2 / 16
PR-method	94.07%	9 / 16
SSU-method	96.69%	9 / 16
PRU-method	99.98%	15 / 16

2) EXPERIMENTAL SETTINGS FOR TECHNIQUE 2

A dimension table was prepared for the set of similar parametric shapes extracted by technique 1, by aligning the orientation of shapes within the set using technique 2, identifying similar locations, and then developing the parametric model. Fig. 13 shows examples of the targets for parametric modeling.

B. RESULTS

1) RESULTS FOR TECHNIQUE 1

Table 1 lists the results of retrieving similar parametric shapes. As shown in Table 1, the accuracy rate of the SS-method (conventional method) is 62.54%; two out of 16 types are classified without mixing of other shapes. The PR-method has a better accuracy rate of 94.07%, as nine types are classified without mixing other shapes. The SSU-method has a further improved accuracy rate of 96.69%, as nine types can be classified without mixing with other shapes. The accuracy rate of SSU-method is higher than that of PR-method because the parametric relationships in each axial direction are emphasized by the conversion to the unit shape. Furthermore, with the PRU-method, the accuracy rate is 99.98%, and 15 types are classified without mixing with other shapes. In addition, the results show that the PRU-method can classify parametric shapes with higher precision than the conventional method.

Next, Fig. 14 shows an example of similarity between the shapes in the SS-method and PRU-method. The dataset contains 99 shapes with the same parametric relationships as the target shape in Fig. 14. In the SS-method, other shapes

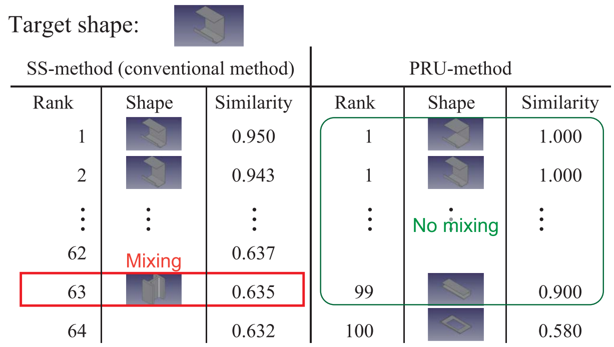

FIGURE 14. Comparative examples of similarity between SS-method and PRU-method. In the dataset, 99 shapes exists with the same parametric relationships as the target. In the SS method, other types of shapes are mixed in the 63rd shape. In the PRU method, no other types of shapes are mixed up to the 99th shape.

are mixed in the 63rd shape, whereas in PRU-method, all data are batch-extracted at a high order. No other types of shapes are mixed up to the 99th shape. In addition, the similarities of the 99th and 100th shapes in the PRU-method are clearly different. Thus, by using the PRU-method, it is possible to detect the differences between 3D shapes based on parametric relationships. Finally, Fig. 15 shows that the L-shapes shown in Fig. 2 are classified as a group of shapes with the same unit shape.

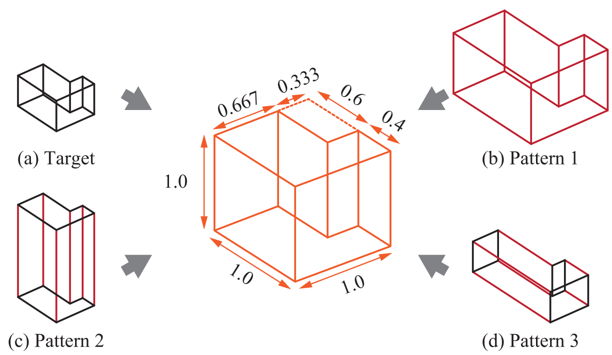

FIGURE 15. Unit shape of target and patterns 1–3. The L-shapes shown in Fig. 2 are converted into the same unit shape and classified into the same group.

2) RESULTS FOR TECHNIQUE 2

Fig. 16 shows some results of constructing parametric models using a set of similar parametric shapes for each target shown in Fig. 13. The formula shown at the top of each 3D graph is one of the obtained parametric models of each shape. Here, in (a), (b), and (e), they are the dimensions in the Z direction, in (c), it is the dimension in the Y direction, and in (d) and (f), they are the dimensions in the X direction. By using this method to extract 3D shapes with a parametric relationship, assuming correspondence of parts between shapes, and using the set of dimension variables V summarizing the dimensions, we demonstrated that it is possible to develop parametric models. The parametric models allow us to change the dimensions of explanatory variables, whereby other dimensions are updated in conjunction, and new shapes with the

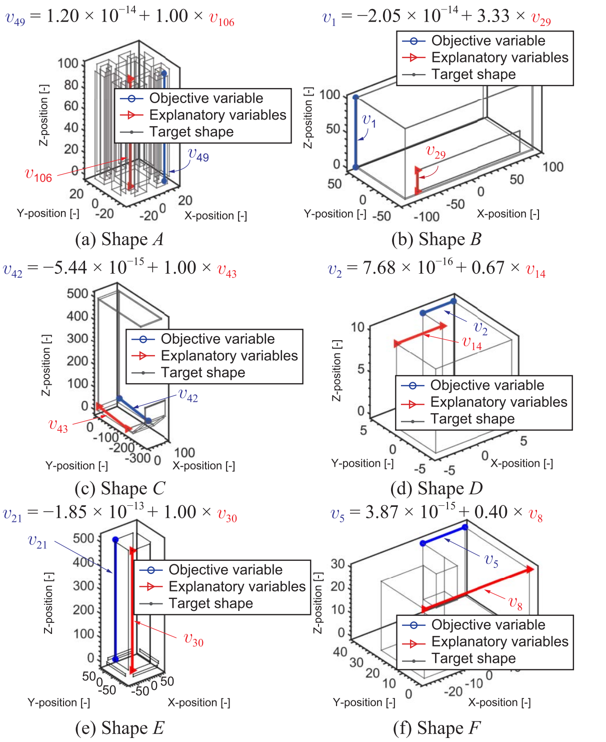

FIGURE 16. Examples of the constructed parametric models. The parametric models of shapes $A - F$ in Fig. 13 are shown. In each 3D graph, the red line is the explanatory variable, the blue line is the objective variable, and the black line is the target. The formula shown at the top of each 3D graph is one of the parametric models of each shape.

same parametric relationships as targets can be automatically designed.

VI. DISCUSSION

A. EVALUATION OF THE PROPOSED METHOD

To collect 3D shapes with the same parametric relationships from a design database, we proposed a framework of converting all 3D shapes into unit shapes, retrieving 3D shapes from the database based on parametric relationships, and developing parametric models by statistical methods. This framework was evaluated using the shapes in a prepared database. The results in Section V show that the PRU-method has much higher classification accuracy than the conventional method using SS-AI to search based on the similarity of a shape. Considering the conventional and PR-methods, we can confirm that classification based on parametric relationships is possible through learning with parametric relationships. In addition, the conversion to unit shapes improved the accuracy of the SSU-method and PRU-method. Mixing of other shapes tends to occur in the conventional classification method owing to the similarity of shapes with elongated 3D shapes, in which the aspect ratio of the shape increases in 2D images. However, by converting the shape into a unit shape, the aspect ratio can be reduced, and the features of the images can be better discriminated, thus improving the accuracy. According to the aforementioned analysis, both PR-method and SSU-method are very effective even when used individually. The PRU-method, which combines both, is the most effective. In the PRU-method, the corresponding parts between the extracted similar parametric shapes are automatically identified using the unit shapes, and parametric models are constructed by MRA using the extracted dimensions as variables. However, in the PR-, SSU-, and PRU-methods, if the target shape is more complicated than those shown in Figs. 9 and 13, the image resolution may be insufficient and the classification accuracy may be low as in the conventional method. As the developed parametric models incorporate the design knowledge included in past design data, the usage of this parametric model is considered to lead to the improved design quality of new designs. The parametric models developed by this method can classify design data in the design database and can be used as standard shapes.

B. FUTURE WORK

In this paper, the applicability of the technique that extracts the 3D shapes based on the parametric relationships was presented, and the parametric modeling technique using the dimensions as variables explained. In Section V, similar parametric shapes were extracted for the 3D shapes mainly composed of straight lines including curves, and the parametric modeling technique is demonstrated for the straight parts of the extracted 3D shapes. In future, we plan to develop a method to construct the parametric models of curved sections such as arcs and holes by using the coordinates of both end points of the curves and the radius and center coordinates of the arcs from the CAD data of each 3D shape, as well as to verify the parametric modeling technique for the curves of 3D shapes. In parametric modeling, if the relationships among the dimensions are nonlinear, new explanatory variables multiplied by each explanatory variable should be introduced into (10). In addition, the correspondence to parametric models in which discretely peculiar shapes repeatedly appear depending on the shape size needs to be studied in the future.

VII. CONCLUSION

The ultimate objective of this study is to automate structural design using parametric models. As the first step, we proposed a framework for parametric modeling. A set of 3D shapes within a design database and targets for parametric modeling were converted to unit shapes through axial normalization during preprocessing, and thereafter, parametric shapes similar to targets were extracted based on the calculated features using the developed PRU-AI. The corresponding parts between a target and similar parametric shapes were identified and their dimensions were extracted as variables. Finally, parametric models were automatically constructed using a statistical method. To demonstrate our framework and its parametric modeling, we extracted similar parametric shapes from a database of various 3D shapes. The results showed that similar parametric shapes were extracted with high accuracy, and parametric models were automatically generated heuristically from the similar parametric shapes. The effectiveness of the proposed framework was verified.

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