

User-Adaptive Sketch-Based 3-D CAD Model Retrieval

Yong-Jin Liu, Xi Luo, Ajay Joneja, Cui-Xia Ma, Xiao-Lan Fu, and Dawei Song

Abstract—3-D CAD models are an important digital resource in the manufacturing industry. 3-D CAD model retrieval has become a key technology in product lifecycle management enabling the reuse of existing design data. In this paper, we propose a new method to retrieve 3-D CAD models based on 2-D pen-based sketch inputs. Sketching is a common and convenient method for communicating design intent during early stages of product design, e.g., conceptual design. However, converting sketched information into precise 3-D engineering models is cumbersome, and much of this effort can be avoided by reuse of existing data. To achieve this purpose, we present a user-adaptive sketch-based retrieval method in this paper. The contributions of this work are twofold. First, we propose a statistical measure for CAD model retrieval: the measure is based on sketch similarity and accounts for users' drawing habits. Second, for 3-D CAD models in the database, we propose a sketch generation pipeline that represents each 3-D CAD model by a small yet sufficient set of sketches that are perceptually similar to human drawings. User studies and experiments that demonstrate the effectiveness of the proposed method in the design process are presented.

Note to Practitioners—Engineering data reuse with the incorporation of modeling knowledge is important in product design. In this paper, a new model retrieval method is proposed in which two challenging issues are addressed. First, pen-based sketching is widely gaining popularity for communicating design ideas. To accommodate this emerging trend, a method that can match a possibly partial free-form sketch to existing detailed 3-D CAD models would be of tremendous use to product design teams. Second, in a human-centered design environment, design tools should have a capacity to adapt to users' individual habits. By using a statistical user profile model to continually learn their drawing habits,

the CAD model retrieval method proposed in this paper presents a new and effective solution for user-adaptive model retrieval.

Index Terms—3-D CAD model retrieval, conceptual design, sketch generation, sketch similarity.

I. INTRODUCTION

WITH the advance of CAD/CAM/CAE techniques, 3-D digital CAD models are widely used at all stages in product lifecycle management. Large databases of existing 3-D models are a strategic information tool for any enterprise involved in design. Therefore 3-D CAD model retrieval has attracted much research attention in the last decade. If textual descriptions are available in the database, finding models therein can be done quickly by standard text retrieval methods. Unfortunately, massive amount of semantic information would have to be attached to geometric models in order to discriminate between different models [24] and therefore text-based retrieval is not a practical method for 3-D CAD models.

Most existing 3-D CAD model retrieval methods utilize inputting a 3-D model or a detailed 2-D engineering drawing to find similar 3-D models in a database. In this work, we study 3-D CAD model retrieval during the conceptual design process. At this stage, the user (i.e., a designer) probably has an idea what he/she is looking for, but does not have any 3-D models or detailed engineering drawings at hand. Traditionally, in conceptual design, users sketch their ideas on paper. Later, these sketches are refined by adding more details and eventually converted into engineering models with full dimensional constraints. As product generations are introduced at higher frequencies, the ability to reuse existing model data is critical. In this paper, we propose a new 3-D CAD model retrieval method based on 2-D pen-based sketch input.

Pen-based sketching is regarded as a natural way to express the user's intent in a visual form [16]. To be effective in rapidly drafting and communicating design ideas between people, the sketches drawn by a designer have two characteristics. First, any sketch is a sparse, simple line drawing. Second, any sketch for conceptual design contains some functional forms such as feature lines of shape, relative positions of functional units, and their global layout, which satisfies the design principles in visual communication [1]. In this paper, we assume that the user is familiar with graphical communication for engineering and a user's sketch is a simple line drawing in a raster form.

Given a user's sketch as input, we want to find the most similar 3-D CAD models in the database. One major challenge in this sketch-based 3-D CAD model retrieval is how to represent CAD models in a database by a suitable format that makes the sketch-based retrieval feasible. In this paper, based on the recent

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advances [11], [12] of line drawing algorithms for 3-D model illustration, we propose a sketch generation pipeline that represents a 3-D CAD model by a small yet sufficient set of representative sketches that are perceptually similar to the sketches drawn by a person.

2-D sketches are merely a rough approximation of the shape of the target design. Consequently, image retrieval methods cannot be directly used for sketch retrieval, since 2-D sketches usually contain much fewer image features than those in natural images. Furthermore, sketches can undergo severe elastic deformations while remaining perceptually similar [6]. In this paper, by unifying both 3-D CAD models and users' input by a sketch representation, we propose a user-profile-adaptive statistical modeling approach for sketch similarity measurement. Different users may have different sketching habits. One major advantage of the proposed statistical modeling approach is that a system using it can adapt itself to different users based on their individual characteristic styles.

Recent neuroscience research [31] reveals that sketching using the line drawing form may exploit the underlying neural codes of human vision. As an effective way to communicate message between designers, sketches may find a wide range of applications in design automation in manufacturing industry [17]. By mapping a user's sketch directly to the engineering models in the database, the wealth of model semantics across product families and lifecycles can be used as early as in the conceptual design stage [21], [24]. Since user's sketches are usually fuzzy and inaccurate, this mapping through retrieval to the detailed product semantics may also offer a new way for knowledge recovery and reuse in product design and assembly [7], [35]. By taking user's behavior into consideration, the user-adaptive sketching model developed in this paper also offers a preliminary study on cognition in production systems [3]. To summarize, in this paper, we propose a new 3-D CAD model retrieval method that uses a 2-D pen-based sketch input to reflect the user's design intent and is suitable in a conceptual design process in which no prior 3-D CAD models or detailed engineering drawings are available. In particular, two contributions are made.

- A statistical modeling approach is proposed for sketch similarity measurement, which can be tailored to any individual sketching style.
- A sketch generation pipeline is proposed that converts every 3-D CAD model in a database into a small yet sufficient set of representative sketches that are perceptually similar to a person's drawings.

II. RELATED WORK

Most companies in the manufacturing industry now have massive libraries of 3-D CAD models that are readily available for use by designers. However, model retrieval by matching some particular shape or form from such a library is challenging. We can categorize different approaches of model retrieval based on the types of inputs that such a system requires. First, CAD models can be represented by different feature types [24], including design features, machining features, and assembly features, etc. In this study, we mainly consider the shape based retrieval, i.e., 3-D CAD models are characterized

by their geometric and topological information such as holes, pockets, fillets, chamfers, and the adjacency relations between them. By concentrating our work on shape-based retrieval in a design process, the retrieval methods can be grouped into two categories, depending on whether the input is 2-D data or 3-D data.

For a 3-D-input and 3-D-output retrieval, how to encode the 3-D design features with effective shape signatures is critical. Many 3-D shape signatures have been proposed and notably they can be classified into global and local ones. A typical 3-D global shape signature that effectively depicts design features is the attributed graph representation [13]. The nodes in an attributed graph represent part surfaces and the edges are part edges. The attributed graph itself encodes the model topology and attributes encoding parts' geometry are typically attached to the nodes and edges in the graph. The local shape signatures utilize the local model structure by segmenting 3-D models based on design and assembly features. Several representative local shape descriptors obtained from a scale-space decomposition had been proposed in [5] and [23]. One advantage of using the local shape descriptor is its support of partial matching.

A few works exist in a 2-D-input and 3-D-output retrieval style. One of the earliest 3-D model retrieval methods with 2-D input was proposed in [15], in which every stored 3-D model is preprocessed into 13 2-D orthographic views. Then, 3-D models are retrieved by matching the user's sketches to the 2-D images of 13 views. Using a fixed number of representative views regardless of the model complexity, however, is obviously not optimal. Pu *et al.* [28] proposed a sketch-based retrieval that requires a user to draw three orthogonal 2-D views of a 3-D model as input. However, it is difficult for a user to sketch three orthogonal drawings consistently as in a formal engineering drawing. Wang *et al.* [32] proposed a method that retrieves 3-D CAD models using both geometric (called 2-D outline) and topological (called 2-D skeleton) information. This approach requires users to provide a skeleton sketch and three 3-D outline sketches, and thus suffers from the same inflexibility as in [28]. In this paper, we propose a 3-D CAD model retrieval method in which a user can freely sketch any shapes in a single line drawing form (i.e., it does not need three consistent sketches from orthogonal views as input) and thus offer a more flexible and useful way for retrieval.

Since we use pen-based free-form sketches for 3-D CAD model retrieval, feature extraction and representation for sketched shape are important. Here we draw attention to other retrieval applications which also use sketch input. As a natural and concise visual form of 2-D shape, sketches have been used in image and video retrieval for many years. A representative work in [6] models users' sketches as closed silhouettes and matches them to the edges in the image using a similarity measure defined by the degree of matching and the elastic deformation energy. Chalechale *et al.* [8] proposed to use an angular-spatial distribution of pixels in the abstract images (akin to the sketches used in this paper) as a compact and effective feature for a sketch-based image matching. Similar to the angular partitioning of abstract images, the shape context descriptor proposed in [4] utilized a histogram in log-polar space that actually leads to a histogram with partitioning along

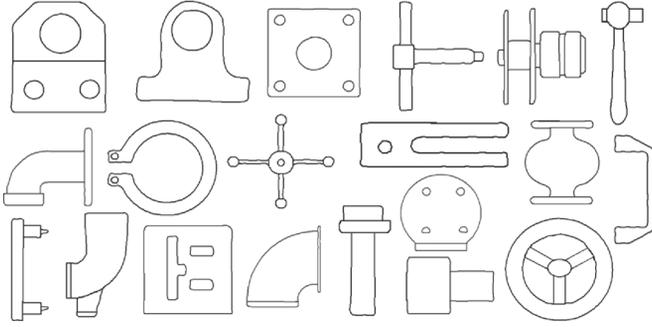


Fig. 1. Some examples of pen-based sketches drawn by users.

the angular and radial directions in the image space. Inspired by the work in [4], [8], [26], in this paper, we propose to extract features in sketches for shape matching using a radial-partitioning-based histogram.

The remainder of this paper is organized as follows. The feature representation of pen-based sketches and corresponding shape matching mechanism is proposed in Section III. Given the sketch-based shape matching mechanism, we present a sketch generation pipeline in Section IV that generates an efficient sketch representation for each 3-D CAD model in database. After briefly outlining a working retrieval system, Section V presents the detailed user study and experimental results that show the advantage of the proposed retrieval style. Finally, our concluding remarks are presented in Section VI.

III. VISUAL WORD REPRESENTATION AND CAD MODEL MATCHING WITH SKETCHES

Sketching or drawing is a complex design activity involving perceptual and conceptual capacities [16]. When a user sketches a 3-D object, some aspects of geometric structures of 3-D objects as well as aesthetic criteria will be used to represent the 3-D object in a recognizable manner. A wide variety of drawing techniques to convey shape information was investigated in [34]. In this study, we follow the assumptions in [11] and [12] that a user's sketch is in the form of simple line drawing including only feature lines, i.e., no hatching lines or stippling for shading/toner effects. Some users' sketches collected in this study are shown in Fig. 1. The proposed sketch-based retrieval method is outlined in the following three steps.

- Step 1) A given database of CAD models are converted into a set of representative sketches, and a set of visual words are created in a vocabulary to describe these sketches (Sections III-B and IV).
- Step 2) The weighting of visual words in the vocabulary is determined by a user profile based on user's sketching history (Section III-C).
- Step 3) When a user draws a sketch for retrieval, the input sketch is converted into a vector of word appearance (Sections III-A and III-B), which is compared with the existing database to find likely model matches (Section III-D).

Our retrieval approach using visual words in sketches is motivated by the success of recasting the object recognition problem as a text retrieval problem [29]. Visual words can be used to formulate strategies analogous to text retrieval for sketch retrieval.

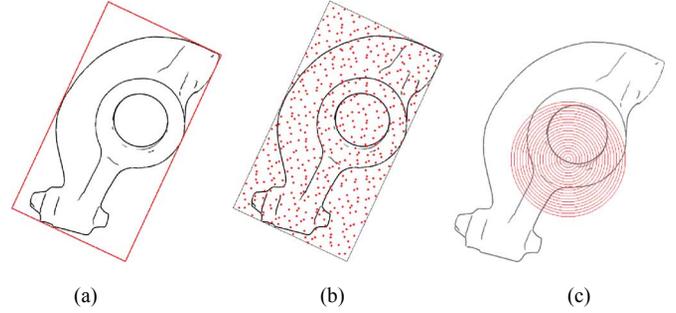


Fig. 2. Feature representation of a sketch. (a) Minimum-area enclosing box of the sketch. (b) Five hundred samples of a quasi-random point sequence. (c) Twenty circular bins of one sample point.

By parsing documents into words, very commonly occurring words that appear in most documents can be discarded. The remaining words that are discriminating for a particular document are assigned unique identifiers. Each document is thus represented by a vector whose elements are integers that give the occurrence frequencies of the words contained in it. A document is finally retrieved by ranking the discrepancy of vectors representing the models in a database.

A. Feature Representation of Sketches

We represent a sketch by a black-and-white line drawing, where black pixels illustrate the sketched shape. To obtain the property of rotation invariance, we find the minimum-area enclosing box of a sketched shape (denoted as B) [Fig. 2(a)] in linear time using the rotating caliper method [30]. We then apply a quasi-random point sequence [18] to uniformly sample n_s points inside B [Fig. 2(b)]. Choosing a large enough value of n_s yields a good balance between the number of total visual words and the accuracy of sketch description. In our experiments, setting n_s to 500 gave the best results.

Centered at each sample point, we locate a circle of radius r being one fifth of the diagonal length of B . We partition the radius r into 20 equal intervals and thus determine 20 concentric circles $\{c_1, c_2, \dots, c_{20}\}$ [Fig. 2(c)]. Each pair of successive circles (c_i, c_{i+1}) forms a radial bin b_{i+1} (the first bin b_1 is bounded by c_1 only). We compute a feature vector for each sample point using the 20 bins:

$$\mathbf{f}(i) = \{\#p_k \in b_i, i = 1, 2, \dots, 20\}$$

where $\mathbf{f}(i)$ is the i th element of the vector \mathbf{f} , p_k represents black pixels constituting the sketched shape, and $\#p_k$ is the number of black pixels falling into bin b_i . We choose the radial-bin-based 20-vector form for sketch-based feature representation, for the following reasons.

- Since the sketching of a person's mind is usually inaccurate and incomplete, shape representation and matching are more appropriate in a local context, and, accordingly, a rich local shape descriptor is better for partial shape matching.
- Given each sample point s as the center of a local disk D , the vectors of black pixels in D pointing to s are proxies for local shape description and have been widely used for shape matching [4], [15], [20]. A full set of vectors carries too much detail and is redundant. Therefore, we choose 20

bins to quantize them. Since sketching is inaccurate, repeated sketches of the same shape frequently show local distortion like angular squeezing or stretching. Thus, we only keep the radial information in our feature representation which is insensitive to such angular variations.

Our feature vector representation is somewhat similar to the shape context descriptor in [4], but with the following major differences. The shape context method [4] uses a set of points to represent a shape and assigns each point a tangent vector. The tangent vector is used to determine the necessary orientation for the shape context descriptor at each point. Accordingly, the shape context descriptor is better suited in the scenario that the shape is representable by a single closed silhouette, so that each silhouette point can be assigned with a consistent tangent vector. In contrast, our feature vector representation does not contain angular information and can be used to represent a large range of sketched shapes, e.g., shape containing occluding contours and ridge-and-valley-like edge features, in addition to silhouettes.

Fig. 3 shows three sketches and three corresponding feature vectors. The first two sketches are based on the same CAD model, in which one is generated by applying the line drawing algorithm on the 3-D CAD model and the other is drawn by a user. The last sketch is for a different CAD model. As demonstrated in Fig. 3, our method generates the similar feature vectors for the sketches about the same CAD model and the sketches from different CAD models have different feature vectors.

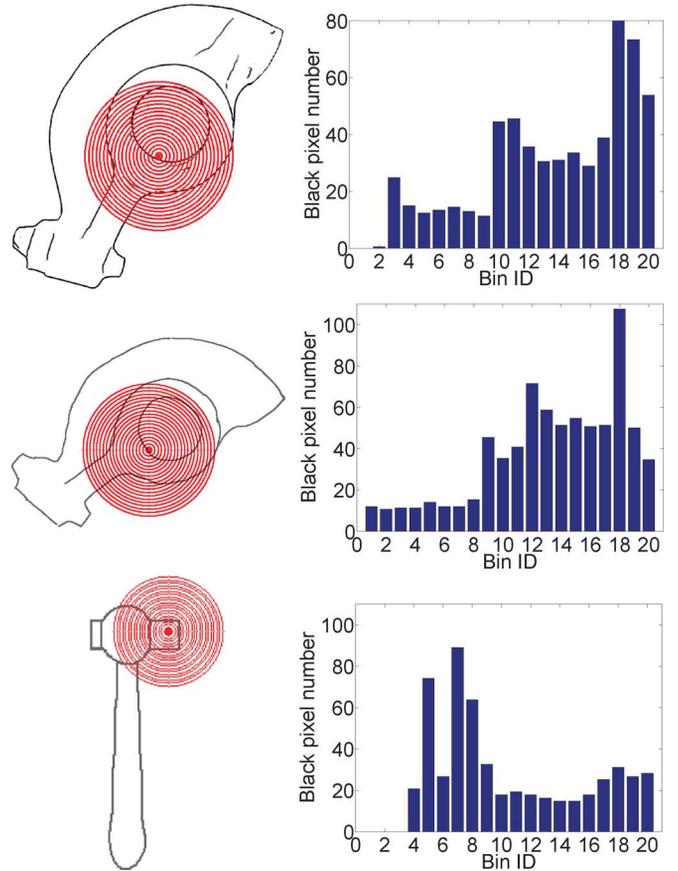


Fig. 3. Three sketches and the feature vectors of the corresponding random points. The first sketch (top row) is generated by applying the line drawing algorithm on a 3-D CAD model (Fig. 5). The second sketch (middle row) is drawn by a user for the same CAD model and the third sketch (bottom row) is about another CAD model.

B. Vocabulary of Visual Words

Based on the sketch feature presentation, we convert a given CAD model database into a vocabulary of visual words as follows.

- Step 1) Each CAD model in the database is converted into a small yet sufficient set of sketches using the SCC method proposed in Section IV.
- Step 2) For all sketches in the database, feature vectors are generated and clustered into visual words.

To implement step 2), we first define a dissimilarity measure between two feature vectors. Since sketches are inaccurate, it is desirable that this measure is insensitive to small geometric perturbation. For example, let \mathbf{f}_{left} be a feature vector that has nonzero values only at bins 2 and 18 [Fig. 4(a)]. If we slightly shift values in \mathbf{f}_{left} to a feature vector \mathbf{f}_{mid} that has nonzero values at bins 3 and 19 [Fig. 4(b)], then it is desired that \mathbf{f}_{left} and \mathbf{f}_{mid} have small dissimilarity values, and they should both have large dissimilarity values to a feature vector $\mathbf{f}_{\text{right}}$ that has nonzero values at bins 2 and 3 [Fig. 4(c)]. However, traditional Euclidean distance such as L_2 norm give a counter-intuition on this observation, i.e., $L_2(\mathbf{f}_{\text{left}}, \mathbf{f}_{\text{mid}}) = 1.41$ and $L_2(\mathbf{f}_{\text{left}}, \mathbf{f}_{\text{right}}) = 1.0$. In this work, we use a general form of inner product [33]:

$$D(\mathbf{f}_1, \mathbf{f}_2) = \mathbf{f}_1^T M \mathbf{f}_2 \quad (1)$$

where M is a symmetric, positive definite matrix with elements

$$m_{ij} = \frac{1}{2\pi\sigma^2} e^{-\frac{(i-j)^2}{2\sigma^2}}.$$

The metric (1) takes spatial relation of bins into account (i.e., values in adjacent bins have higher possibility to affect each other). We use $\sigma = 0.5$ in our study. For the three feature vectors shown in Fig. 4, $D(\mathbf{f}_{\text{left}}, \mathbf{f}_{\text{mid}}) = 0.354$ and $D(\mathbf{f}_{\text{left}}, \mathbf{f}_{\text{right}}) = 0.40$. For the three feature vectors shown in Fig. 3, $D(\mathbf{f}_{\text{top}}, \mathbf{f}_{\text{mid}}) = 0.313$ and $D(\mathbf{f}_{\text{top}}, \mathbf{f}_{\text{bottom}}) = 0.75$. Note that in all dissimilarity computation, the feature vectors are normalized since the vector magnitude is affected by thickness of sketched lines and the direction of feature vector is much more informative.

In Section IV, we present a pipeline that converts a 3-D CAD model into a set of representative sketches. Since each sketch is represented by 500 feature vectors, we can regard that the database consists of a large number of feature vectors. Based on the dissimilarity metric (1), we then cluster these feature vectors into visual words which constitute a visual vocabulary.

Most clustering algorithms partition the data into m clusters, where the number m is fixed as a known *a priori*. However, an optimal cluster number m is often difficult to be predefined. Frey and Dueck [14] proposed a method called affinity propagation (AP), in which the number of clusters can be automatically and optimally determined. We adopt a variant of the AP method to cluster the feature vectors into visual words, each of which is the center of a cluster.

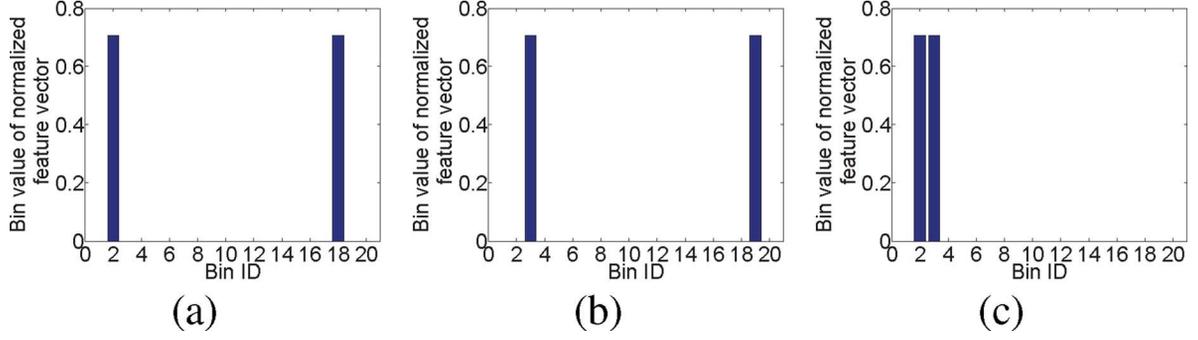


Fig. 4. Three different feature vectors, with equal magnitude non-zero values in: (a) bins 2 and 18, (b) bins 3 and 19, and (c) bins 2 and 3. (a) \mathbf{f}_{left} . (b) \mathbf{f}_{mid} . (c) \mathbf{f}_{right} .

Suppose that the vocabulary has m visual words, i.e., $V = \{w_1, w_2, \dots, w_m\}$. Recall that a sketch has 500 feature vectors. If a feature vector falls into the cluster of word w_i , then the occurrence of w_i is increased by one. This operation simulates the keyword representation in a text document searching, i.e., the words “sketches,” “sketching,” and “sketched” are all represented by one keyword “sketch.” Then a sketched shape can be represented by the vocabulary as $S = \{n_1 w_1, n_2 w_2, \dots, n_m w_m\}$, where n_i is the occurrence of visual word w_i in that sketch and $\sum_{i=1}^m n_i = 500$.

C. User Profile Model of Individual’s Sketches

Most previous work in document retrieval [2] has all words of the same importance. However, different users may have different drawing habits, that is, the user may be used to some particular local drawing patterns (akin to using some particular words more frequently in writing documents) and thus some visual words are more important than others in vocabulary for that user. In this study, we take a user profile model into account for weighting the visual words, which can be outlined in two steps.

- Step 1) Initially, each visual word in the vocabulary is assigned an equal weight.
- Step 2) Based on the user’s sketching history, the visual words favored by user’s drawing habits are determined and assigned a possibility measure. For future sketching, the final weighting of all visual words is inferred by the stationary distribution of a Markov chain model.

The user profile model records the sketches drawn so far by the user. Let F be all feature vectors of these sketches. We convert F into visual words as $S(F) = \{n_1(F)w_1, n_2(F)w_2, \dots, n_m(F)w_m\}$, where each visual word w_i occurs $n_i(F)$ times and has $n_i(F)$ feature vector instances $F_i = \{\mathbf{f}_1^i, \mathbf{f}_2^i, \dots, \mathbf{f}_{n_i}^i\}$. In the rest of the paper, we use n_i for $n_i(F)$ for brevity. Given $S(F)$, it can be inferred that the user has a tendency to use some words more frequently (those with larger values of n_i) and others less frequently (those with smaller value of n_i). We make the assumption that all visual words in the vocabulary are irreducible and each word occurs at least once. So if $n_i = 0$ for some visual word w_i in $S(F)$, we set $n_i = 1$ and let the corresponding feature vector instance being the visual word w_i itself.

In a user profile, the vocabulary V is regarded as a state space and each visual word $w_i \in V$ is a state. Let $\lambda = \{\lambda_i : w_i \in V\}$ be a possibility measure on V , where $\lambda_i \geq 0$ is the possibility of visual word w_i being representative for user’s sketching habits. We set the total mass $\sum_{w_i \in V} \lambda_i = 1$ and λ define a distribution of a random state X that take possibility λ_i for the state w_i .

We regard the sketching process by a user as a sort of stochastic process, in which the representative visual words are not fixed but dynamically changed.¹ We model this dynamism by adding an artificial discrete time t to the distribution X_t and setting the transition probability p_{ij} between any two visual words w_i, w_j by their similarity as

$$p_{ij} = \frac{s_{ij}}{\sum_{j=1}^m s_{ij}}$$

where

$$s_{ij} = D_{ij} - \frac{1}{n_i} \frac{1}{n_j} \sum_{\mathbf{f}_u \in F_i} \sum_{\mathbf{f}_v \in F_j} D(\mathbf{f}_u, \mathbf{f}_v)$$

$$D_{ij} = \max\{D(\mathbf{f}_u, \mathbf{f}_v), \forall \mathbf{f}_u \in F_i, \forall \mathbf{f}_v \in F_j\}$$

and $D(\cdot)$ is defined in (1). The transition matrix $\mathbf{P} = (p_{ij} : 1 \leq i, j \leq m)$ is stochastic, since every row $(p_{ij} : 1 \leq j \leq m)$ is a distribution. Suppose that only the current state of a user’s sketching process can influence where to sketch next.² Then the sketching process $(X_t)_{t \geq 0}$ is a Markov chain with transition matrix \mathbf{P} and the initial distribution is $\lambda_0 = (\lambda_i = n_i/n_{total} : w_i \in V)$, where $n_{total} = n_1 + n_2 + \dots + n_m$ is the total number of feature vectors in F .

We infer the long term properties of a user’s sketching process from the stationary distribution of the corresponding Markov chain model. Since in $S(F)$, each visual word w_i has at least one occurrence, i.e., $n_i \geq 1$, all elements p_{ij} in \mathbf{P} are strictly

¹This treatment is based on the observation that when a user draws the same shape twice, the sketches may be different but similar to each other. This means that some visual words have possibility to transfer to each other and we model this transferability by a Markov chain model.

²This assumption also implies that the state X_m at time m has an indirect influence on the state X_{m+n} at time $m+n$, since

$$\begin{aligned} \mathbb{P}(X_m = i_m, X_{m+1} \\ &= i_{m+1}, \dots, X_{m+n} \\ &= i_{m+n}) \\ &= \lambda_{i_m} p_{i_m i_{m+1}} p_{i_{m+1} i_{m+2}} \dots p_{i_{m+n-1} i_{m+n}}. \end{aligned}$$

positive, and thus the transition matrix \mathbf{P} is irreducible. Meanwhile, since $p_{ij} > 0$, all states in V are reachable, and there must exist some state that is positive recurrent. Then, the user's sketching process is ergodic for which a stationary distribution exists and is independent of initial distribution. Given the ergodic property, the stationary distribution, denoted by λ_∞ , can be efficiently computed as the left eigenvector of the transition matrix \mathbf{P} with eigenvalue 1.

D. Sketch Matching Based on User Profile

The stationary distribution λ_∞ offers an importance measure of visual words in the vocabulary V , for any particular user. Let the visual words in V be sorted into V' according to the possibility in λ_∞ , in a descending order. Denote the subset of the top 30% visual words in V' as I and $nI = V \setminus I$.

Recalling that given a vocabulary V with m visual words, a sketch is represented by $S = \{n_1 w_1, n_2 w_2, \dots, n_m w_m\}$. To introduce an importance measure based on a user profile model, a sketch is now represented by two vectors V_I and V_{nI} as

$$V_I = \left(n_1 \log \left(\frac{N}{n_{1d}} \right), n_2 \log \left(\frac{N}{n_{2d}} \right), \dots, n_k \log \left(\frac{N}{n_{kd}} \right) \right)$$

for $I = \{w_1, w_2, \dots, w_k\}$ and

$$V_{nI} = \left(n_{k+1} \log \left(\frac{N}{n_{(k+1)d}} \right), \dots, n_m \log \left(\frac{N}{n_{md}} \right) \right)$$

for $nI = \{w_{k+1}, \dots, w_m\}$, where N is the number of all sketches in the database and n_{rd} is the number of occurrence of visual word w_r in all sketches in database, $r = 1, 2, \dots, m$. The factor $\log(N/n_{rd})$ is the inverse document frequency [2], [29] which downweights the trivial common words (analogous to "the" or "an", etc. in textual search) in the vocabulary. Finally, given two sketches $S(i) = (V_I(i), V_{nI}(i))$ and $S(j) = (V_I(j), V_{nI}(j))$, their similarity is defined by

$$\text{Sim}(i, j) = (1 - w) \frac{V_I(i) \cdot V_I(j)}{\|V_I(i)\| \|V_I(j)\|} + w \frac{V_{nI}(i) \cdot V_{nI}(j)}{\|V_{nI}(i)\| \|V_{nI}(j)\|} \quad (2)$$

where $0 \leq w < 1$ is a weight to balance the effect of important (V_I) and nonimportant (V_{nI}) visual words, for a particular user profile. In all our experiments, we use $w = 0.2$.

To summarize, our method achieves user-adaptive retrieval results based on the following considerations.

- The vocabulary of visual words is determined by the database of CAD models.
- The importance measure of visual words is determined by a user's sketching history.
- The sketch-based retrieval results are determined by sketch input, the vocabulary of visual words and the importance measure of visual words.

IV. SKETCH GENERATION IN 3-D CAD MODEL DATABASE

To match a user's sketch input, we process and represent each 3-D CAD model in the database by a small yet sufficient set of representative sketches akin to human drawings. To convert a

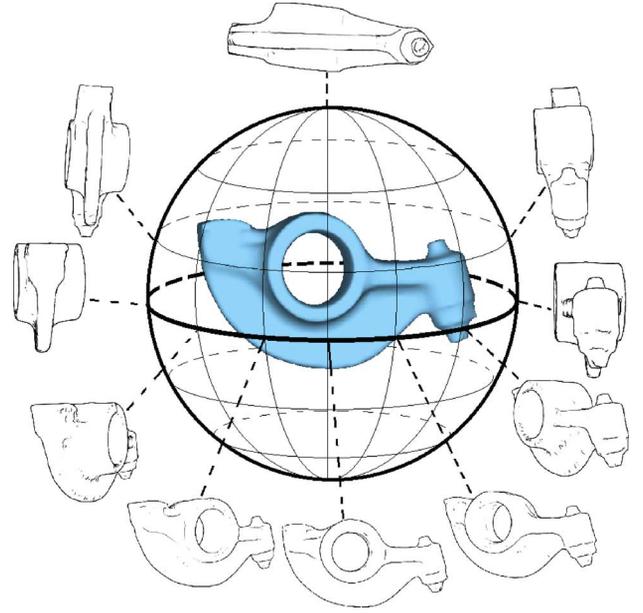


Fig. 5. 2-D sketch generation of a 3-D CAD model using a bounding sphere with a curved mesh on spherical surface. For a clear illustration, only a few viewing directions are drawn in this schematic plot.

3-D CAD model into 2-D sketches, we compute the bounding sphere of the 3-D model and then scale it such that the sphere has unit radius. The center of the sphere is coincident upon the mass centroid of the model. Circles of longitude and latitude with a dense granularity induce a curved mesh on spherical surface. Virtual cameras are placed at the vertices of the mesh and orthographic projections are made along each corresponding direction, i.e., from mesh vertices to the center. Fig. 5 shows an example. Given a viewing direction of a virtual camera, we compute the 2-D projection of the 3-D CAD model.

2-D projection based on the viewpoints from a spherical mesh had been used in image-based 3-D model retrieval, e.g., in [9], but previous work mainly uses silhouettes of 2-D projected images for subsequent retrieval. However, the silhouettes are far from the pen-based sketch input provided by a user and thus cannot be used in our retrieval method. The major difference in our method is to make use of recent advances in line drawing algorithms [11], [12] to represent given 3-D CAD model by sketches akin to human drawings.

Given a 3-D model, Cole *et al.* [11], [12] studied the problem of how humans sketch line drawings to depict perceived shape in a person's mind. In terms of geometry of 3-D model and viewpoints, three line types that convey shape are studied in [12]:

- suggestive contours: occluding contours (also called silhouettes in literature) are places where surface turns from visible to invisible from a viewing direction. Suggestive contours extend the notion of occluding contours by adding visible feature lines where a surface bends sharply away from the viewing direction.
- ridges and valleys: independent of viewing directions, ridges and valleys are sharp geometric features defined by the first- and second-order curvature derivatives on smooth surfaces.

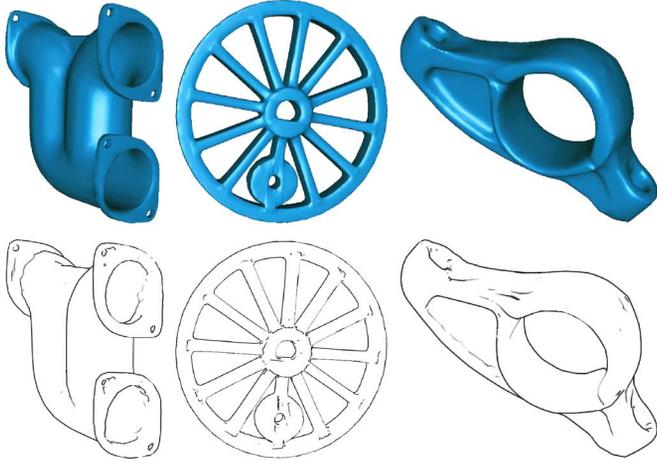


Fig. 6. Three examples of sketch generation of 3-D models using suggestive contours and apparent ridges. Top: three 3-D CAD models in Gouraud shading. Bottom: three generated sketches.

- **apparent ridges:** as a view-dependent extension of ridges and valleys, apparent ridges are defined as the loci of surface points where a view-dependent curvature is maximized. To make the apparent ridges slide smoothly on surfaces when the viewing direction changes smoothly, the view-dependent curvature is defined to be the variation of surface normal with respect to a viewing screen plane.

More than 80% mechanical parts can be designed by applying Boolean operations on a small set of simple geometric primitives, such as cylinders, cones, blocks, spheres and tori, together with a set of blend/offset/fillet/sweep operations. Thus, concerning line drawings, the design features of a 3-D CAD model can be best characterized by geometric features on a surface model. Since we need sketches whose lines slide smoothly over surface with contiguous viewing directions to make a smooth video (Section IV-A), we choose using both suggestive contours and apparent ridges to obtain sketches akin to human drawings. Fig. 6 illustrates three examples of sketch generation of 3-D models from a viewing direction.

A. Sketch Generation Pipeline

We sample the bounding sphere of a 3-D CAD model in both longitude and latitude directions to generate the viewing directions. For each viewing direction, a sketch is generated using a combination of suggestive contours and apparent ridges. If the viewing direction sampling is very dense, there may be incrementally small information gained for sketches along contiguous viewing directions. If the sampling is sparse, some viewing directions of distinct typical sketches may be missed. Obviously, the optimal set of representative sketches for a 3-D CAD model depends on the model's shape complexity. For instance, for a spherical model, one sketch is enough; but for the models shown in Fig. 7, more representative sketches are needed. We propose the following pipeline to generate a small yet sufficient set of sketches for each 3-D CAD model.

- Step 1) Generate a dense sampling on the bounding sphere. Using a 5° interval (in both longitude and latitude directions) generates a total of 2592 viewing directions.

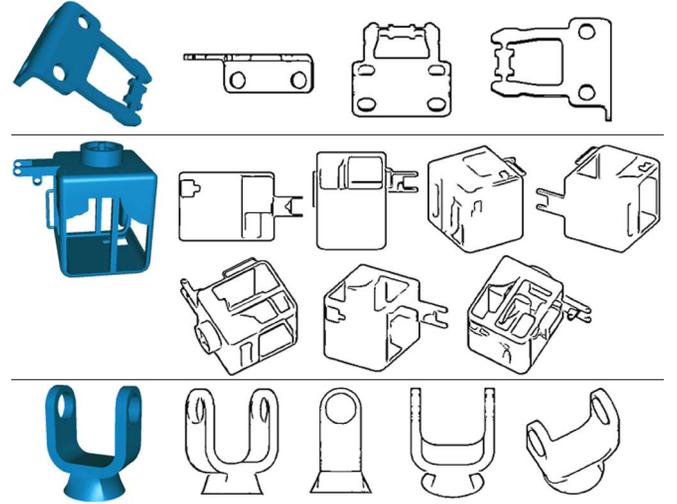


Fig. 7. Representative sketch sets of three models with different complexities. Three 3-D models in Gouraud shading are shown in left column.

- Step 2) For each viewing direction, generate a sketch of the 3-D CAD model using both suggestive contours and apparent ridges.
- Step 3) Assemble the 2592 sketches into a sketch video by recording sketches in a continuous path of viewing directions, that is, by parameterized longitude and latitude directions using (u, v) space, go through all samples (u_i, v_j) in a zigzag path.³ Note that, since we use a combination of suggestive contours and apparent ridges, the lines in sketches slide smoothly over the surface with contiguous viewing directions, and thus the sketch video is smooth.
- Step 4) Extract the keyframes from sketch video using a sufficient content change (SCC) method as presented in Section IV-B.
- Step 5) Output the extracted keyframes as the optimal set of representative sketches.

B. Keyframe Extraction From Sketch Video

We propose a SCC measure of two successive sketches with contiguous viewing directions and use this SCC measure to extract keyframes from sketch video as a representative set of sketches.

Let i, j be two successive sketches, each of which is represented by a set of points (black pixels), i.e., P_i, P_j . Since both the viewing direction and viewing content are changed smoothly, we align the two sketches i, j together by making their local coordinate systems⁴ coincide with each other. We define the sufficient content change $SCC(i, j)$ of sketches i, j by a measure similar to Hausdorff distance but taking all points into account as

$$SCC(i, j) = \frac{1}{\#P_i \#P_j} \left(\sum_{x \in P_i} \min_{y \in P_j} d(x, y) + \sum_{y \in P_j} \min_{x \in P_i} d(x, y) \right)$$

³This path is determined by a two-loop iteration. In the inner loop, u is fixed and v is increasing. Then, in the outer loop, u is increasing.

⁴The local coordinates are determined by the longitude and latitude directions on the tangent plane.

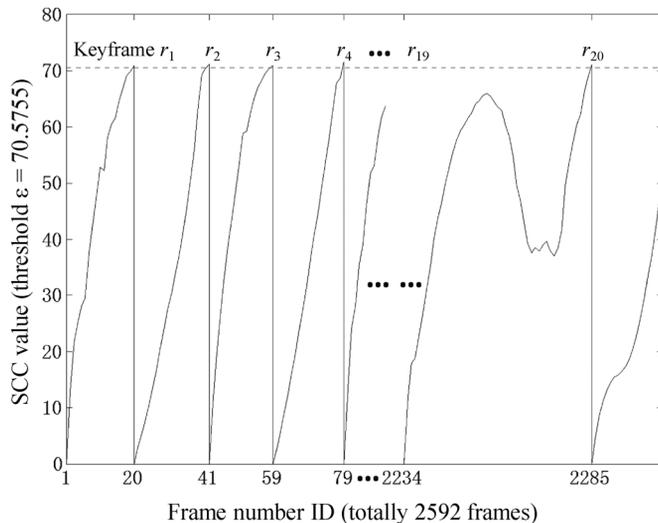


Fig. 8. Keyframe selection for the model shown in Fig. 5 using the SCC method. Once a frame is selected as a keyframe, the SCC value is reset to zero to start another round for selecting the next keyframe.

where $\#P$ is the cardinality of set P and $d(x, y)$ is the distance between two points x, y in aligned coordinate system.

We roughly determine the 3-D model's orientation using the PCA method and set the first frame in sketch video (corresponding to the top view projected from the direction $(0, 0, -1)$) as one keyframe r_0 . Note that our keyframe extraction method below does not require accurate orientations of 3-D models. Refer to Fig. 8. Given a set of keyframes $\{r_1, r_2, \dots, r_i\}$ so far, the SCC method selects the next keyframe r_{i+1} by a linear scanning of the frames f_t after r_i and finding one that satisfies $r_{i+1} = \arg \min_t \{SCC(f_t, r_j) > \varepsilon, j = 1, 2, \dots, i\}$, where ε is the content change threshold. We set ε being one tenth of the maximal SCC value among all frames compared to the first one. The SCC method is fast and two line scans of all frames in sketch video are sufficient to extract the required keyframes. Since the keyframes are selected using a temporal order of image sequence and two keyframes that are not adjacent temporally may still have close geometric positions on viewing directions, we use the AP method [14] to cluster selected keyframes into a representative set of sketches for the 3-D model. Compared to the 2592 frames in sketch video, there are usually a small number of keyframes. In this case, the AP method runs fast in few seconds. Fig. 7 illustrates examples of representative sketches for three CAD models with different complexities.

V. EXPERIMENTS

The proposed retrieval method is composed of an offline and an online module. In the offline stage, the representative sketches for each 3-D CAD model in the database are generated adaptively according to the model's complexity. In each sketch, $n_s = 500$ feature vectors are generated. Suppose there are totally n feature vectors. We use a fixed number $O(\log n)$ of iterations in AP method and then $O(n^2 \log n)$ time is needed to cluster feature vectors into m visual words. In the online stage, the user inputs a sketch and $n_s = 500$ feature vectors

are generated in linear time using the Halton pseudorandom sequence. Converting the input sketch with n_s feature vectors into a visual word representation requires $O(n_s m)$ time. Finally, the similarity indices are provided in $r \log r$ time, where r is the total number of representative sketches in the database.

Based on the proposed method, we implement a retrieval system that consists of a user sketching interface and a database of 3-D CAD models (cf. top of Fig. 13). During preprocessing, the 3-D models in database were converted into representative sketches, generated by the pipeline proposed in Section IV. Based on the generated sketches, feature vectors and visual words were extracted to form a vocabulary, using the method presented in Section III. Initially, all visual words in the vocabulary are assigned the same importance. Then the user sketches some shapes to start the retrieval experience. Given updated user's sketches, a user profile model is established using the method in Section III-C and important and non-important subsets of visual words in the vocabulary are classified offline. Finally by matching user's sketch input with the sketches in the database using metric equation (2) in Section III-D, the retrieval of 3-D models that possess the most similar sketches in the database is adapted to any individual user.

The advantages of the proposed retrieval method are twofold. First, the retrieval style using a single free-form sketch,⁵ based on a user profile model, is attractive and valuable for conceptual design. Second, the sketch-based retrieval by generating representative sketches of 3-D models also has competitive retrieval accuracy among many classical 3-D model retrieval methods. We demonstrate these two advantages using the following retrieval performance experiment (Section V-A) and a user study on user profile models (Section V-B). Finally, applications for sketch-based retrieval are presented (Section V-C). In this paper, all experiments are performed in an off-the-shelf PC (Intel(R) Core(TM) I7-2600 CPU 3.4GHz) running Windows 7, with a Wacom CTH-461 touch drawing tablet.

A. Experiment on the Retrieval Accuracy

In the proposed retrieval method, since the representative sketch forms for the 3-D database are generated in a perceptually optimal way [11], [12], we expect that the retrieval accuracy of the method is high when compared to some well-known 3-D model retrieval methods. The following experiment is performed and the results demonstrate this expectation.

Since most retrieval methods use a 3-D input, for a comparison, we adapt our retrieval method as follows. We use one half of 3-D models as input and the other half of 3-D models as the testing database. Given an input 3-D model, we use the method in Section IV to generate a set of representative sketches for it. Each representative sketch is then matched to the testing database and gives a ranking of the models in the database. The final ranking list is given by averaging on all rankings from all representative sketches.

The performance of the proposed retrieval method, as well as the comparisons to other retrieval methods, are measured by

⁵Previous sketch-based retrieval methods either utilize three orthogonal 2-D sketches [28], or use both geometric (2-D outline) and topological (2-D skeleton) information [32], while our method supports retrieval using a single free-form sketch.

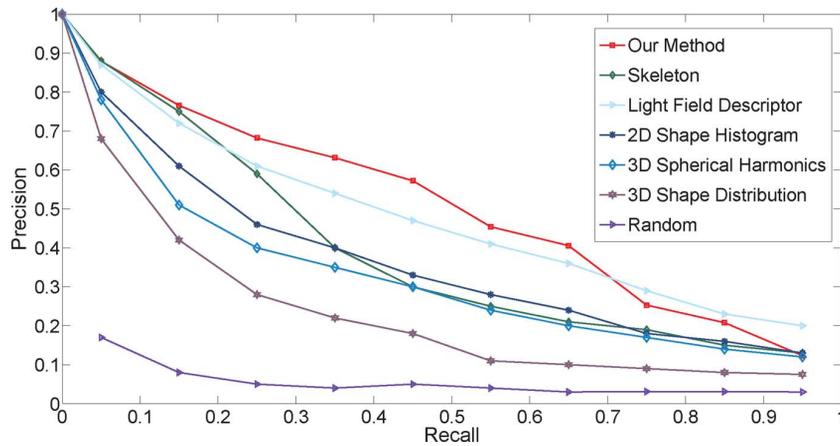


Fig. 9. Precision-recall curves for the comparison of several retrieval methods using ESB database [19]. See Section V-A for details of the seven methods.

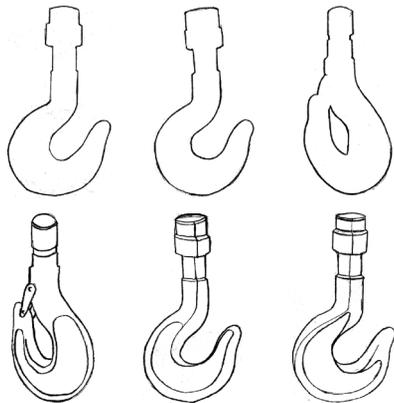


Fig. 10. Sketches drawn by users for design a crane hook. Top: user #1 likes using silhouettes only. Bottom: user #2 likes using internal structure lines as well as silhouettes.

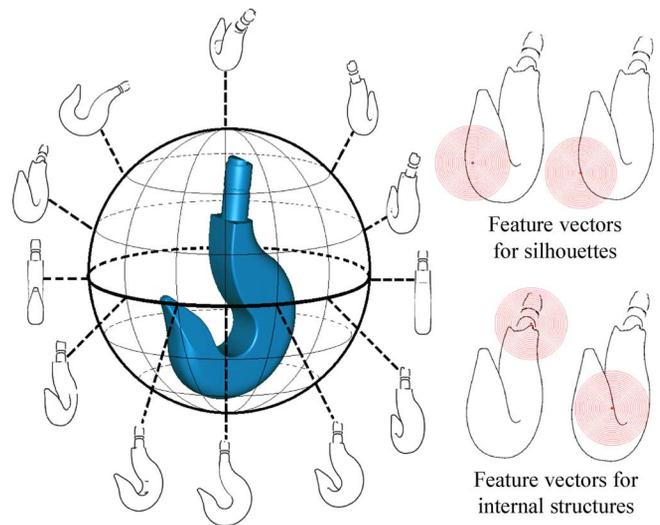


Fig. 11. Sketch and feature representation of a crank hook 3-D model.

employing the precision/recall curve [2]. The term *precision* describes the exactness, and *recall* describes the completeness of the retrieval results. Suppose that a model M is in some category C_M with c members. For the i th retrieved relevant result from the same category ($i = 1, 2, \dots, c$), the recall value is i/c . Given a recall value i/c , ($i = 1, 2, \dots, c$), we find the ranking r of the i th model of this category C_M in the retrieved results and the precision is defined as i/r . For example, the “gear like parts” category C_G in the ESB benchmark has 36 models. If the user sketches a gear, some models are retrieved and ordered according to the similarity values. Let g_5 be the fifth retrieved relevant result in the category C_G and the ranking order of g_5 in the whole retrieved results in the benchmark is 8 (some models in other categories may have a higher ranking than g_5). Then, the recall and precision values of g_5 is $5/36$ and $5/8$, respectively.

We use half of the models as input in turn and the final output of precision/recall curve is averaged over all models’ precision/recall curves. For a perfect retrieval, the precision/recall curve is a horizontal line with precision value of 1. In general, the area enclosed under the precision-recall curve is a good indicator of the retrieval performance, with a higher value indicating better performance.

We use the Engineering Shape Benchmark Database (ESB) in [19] which contains 801 3-D CAD models in 42 categories

for the comparison. Thanks to the ESB benchmark, we could compare the accuracy of our retrieval method with the following methods:

- Skeleton [32]. This method retrieves models with shape descriptor using both geometric and topological information, i.e., the user’s 2-D sketch is matched to models’ views and the skeleton of sketch is matched to the skeletons of models’ views, using an image-based ARP signature. The similarity values for the sketch and skeleton are combined together to report the retrieval results.
- Light field descriptor [9]. This method projects 3-D models into 2-D images and then uses Zernike moments and Fourier descriptors to encode and match the contour information in the 2-D views.
- 3-D spherical harmonics [20]. By embedding a 3-D model into a set of concentric sphere, the 3-D model can be represented by a spherical function and the corresponding spherical harmonic coefficients are used to determine the similarity of two models.
- 3-D shape distribution [15]. In this method, a set of points are generated by randomly sampling the model surface.

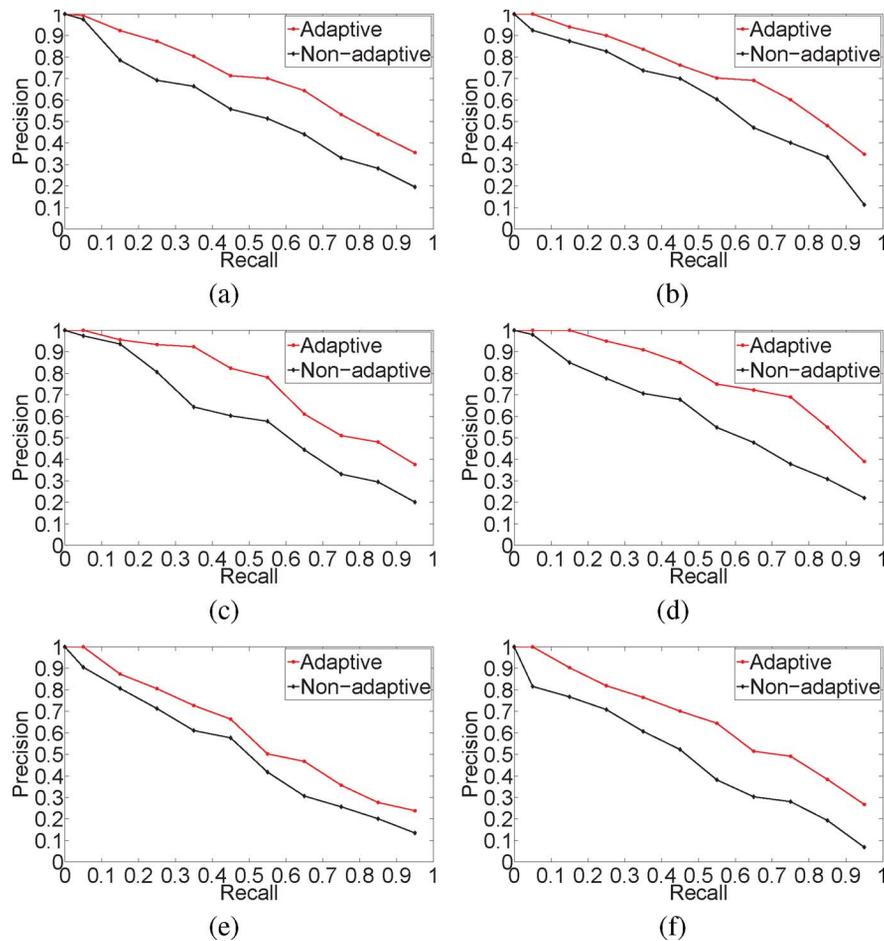


Fig. 12. Precision-recall curves of different users with adaptive and nonadaptive weights in visual words. (a) User #1. (b) User #2. (c) User #3. (d) User #4. (e) User #5. (f) User #6.

The Euclidean distance between each pair of points is computed. A model is represented and matched to other models by using a distribution of these Euclidean distances.

- 2-D shape histogram [28]. After obtaining three orthogonal main views of a 3-D model, Pu and Ramini [28] represent the shape of 2-D views by a distance distribution between pairs of randomly sampled points, which can be regarded as a 2-D version of the 3-D shape distribution [15].
- Random retrieval [15]. Model retrieval by random selection is used in [15] as a baseline for comparison purpose.

The performance comparison of our method with the above methods is summarized in Fig. 9. At the same recall value, the method with a higher precision value retrieves more relevant models and thus has a better performance. As demonstrated by the results shown in Fig. 9, our method and the light field descriptor (LFD) [9] had the best retrieval accuracy for this data set. Furthermore, our method is better on average than LFD and in particular has a higher precision value when the recall value is smaller than or equal to 0.7. Note that although LFD also uses an image-based representation, it cannot support free-form sketch input.

B. Study on the User Profile Model

In the retrieval performance experiments, we use the same weight for all visual words in our method. These weights can

be further tuned for any individual user to capture a user-adaptive behavior. Accordingly, we perform the following user study in which all users were invited from the engineering school. The sketches drawn by two different users, designed for a crane hook, are illustrated in Fig. 10. To represent the design intent, user #1 prefers using silhouettes (the top row in Fig. 10) while user #2 also uses internal structure lines (the bottom row in Fig. 10).

Note that, in our sketch generation and feature representation of sketches (as well as the visual words), both silhouettes and internal structures are characterized (Fig. 11). Given the user input, the Markov chain model will assign different weights to visual words that are adapted to individual user's behavior. The precision-recall curves for users #1 and #2, as well as four other users (i.e., #3 to #6), are presented in Fig. 12, from which we conclude that the adaptive weights according to user's behavior have a better retrieval performance than the nonadaptive weights.

C. Applications of Model Reuse by Sketch-Based Retrieval

Sketching is frequently used in conceptual design [1], [25], [27]. In Supplemental Material A, a user study was presented, showing that for a cone-clutch structure design, retrieval using a single free-form sketch can facilitate the design process. The proposed sketch-based retrieval method emphasizes the usage

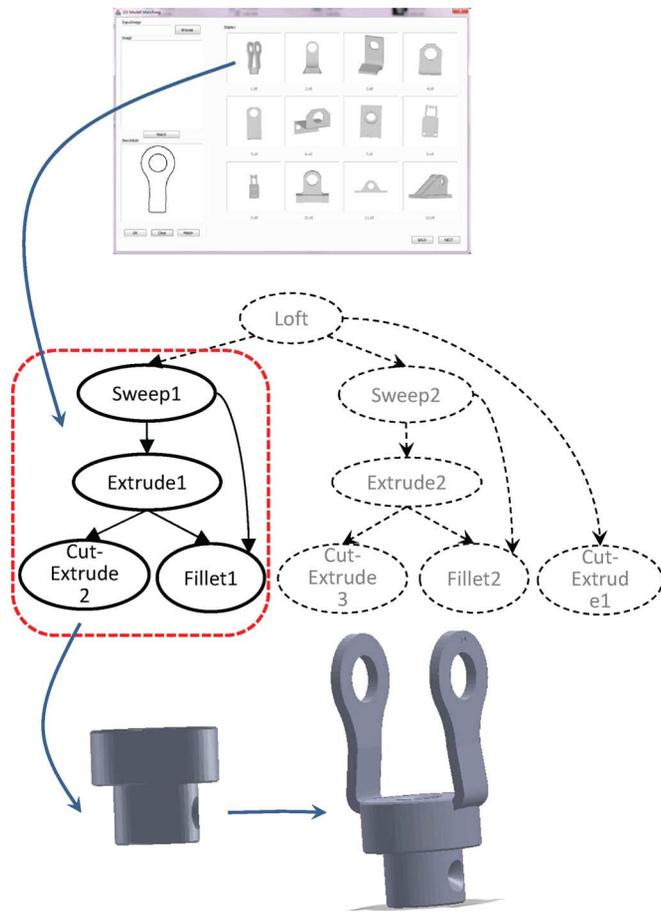


Fig. 13. User's sketch partially matches one 3-D CAD model M . The FDAG of M is extracted and a subgraph of FDAG is applied to another existing 3-D CAD model to generate a new one by model reuse. Full details are presented in Supplemental Material B.

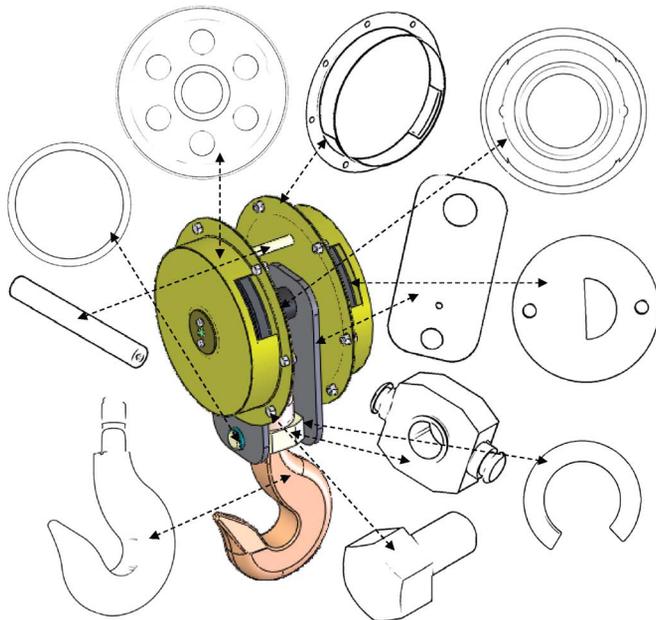


Fig. 14. Crank hook assembly model represented by workpieces' sketches.

of a user profile model and can be adapted to any individual's drawing habits. This key feature makes the proposed method

collaborative with many retrieval-based mechanical design reuse methods (e.g., [10], [22]). In Supplemental Material B, the feature dependency directed acyclic graphs (FDAGs) [22] are used as an example to illustrate how sketch-based retrieval can be used in model reuse. As shown in Fig. 13, by retrieval using subparts' information, a user's sketch can find similar subparts by partial shape matching. Furthermore, if we disassemble a mechanical product into parts and represent each part by representative sketches, then with sketch-based retrieval, user's simple sketches can also have feedback about product assembly information. Fig. 14 illustrates such an example that can be retrieved by the users' sketches shown in Fig. 10. A detailed study on this cross-domain retrieval is beyond the scope of the current work, but is a topic of interest in our continuing work.

VI. CONCLUSION

In this paper, we proposed a new method to retrieve 3-D CAD models with pen-based free-form sketch input. Compared to previously reported methods with sketch-based input that either require three orthogonal views to be sketched [12] or require sketching both outline and skeleton information [13], our method uses simple free-form sketches that naturally express the user's design intent as input.

To capture and match the sketching contents to 3-D models in the database in a perceptually optimal way, we preprocess the database by converting it into a small yet sufficient set of representative sketches that are perceptually similar to human drawings. The representative sketches are generated by a combination of suggestive contours and apparent ridges, and are adapted to models' complexity. Thus, complicated models have more representative sketches while simple models have fewer representative sketches. We also propose a visual word representation to characterize the sketch features and propose a Markov chain model to adapt the sketch-based retrieval to any individual user's habits. A user study and empirical evaluations on retrieval accuracy demonstrate two advantages of the proposed methods: 1) the style of retrieval using simple free-form sketches is valuable and the user adaptability makes the retrieval process more efficient and 2) the perceptually optimized sketch generation and visual word representation for similarity measure make the proposed method one of the best performing retrieval methods in term of retrieval accuracy.

A limitation of the presented method is that a single free-form sketch mainly captures some geometric information. Although sketches can reflect some aspects of users' thought [16], we can further incorporate more semantic meanings into the retrieval process such as using keywords. Along this direction, we will study the multimode-input and cross-domain retrieval in the future work.

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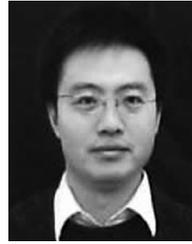
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