

Pose-Inspired Shape Synthesis and Functional Hybrid

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Abstract— We introduce a shape synthesis approach especially for functional hybrid creation that can be potentially used by a human operator under a certain pose. Shape synthesis by reusing parts in existing models has been an active research topic in recent years. However, how to combine models across different categories to design multi-function objects remains challenging, since there is no natural correspondence between models across different categories. We tackle this problem by introducing a human pose to describe object affordance which establishes a bridge between cross-class objects for composite design. Specifically, our approach first identifies groups of candidate shapes which provide affordances desired by an input human pose, and then recomposes them as well-connected composite models. Users may control the design process by manipulating the input pose, or optionally specifying one or more desired categories. We also extend our approach to be used by a single operator with multiple poses or by multiple human operators. We show that our approach enables easy creation of nontrivial, interesting synthesized models.

Index Terms—3D Modeling, Shape Synthesis, Pose-Inspired, Functional Hybrid.

1 INTRODUCTION

SHAPE synthesis, aims to create new shapes, typically by reusing existing models. The recent efforts have been mainly put on designing man-made objects of the same category, by properly interchanging parts with the same semantics [1], [2], [3], or suggesting suitable parts with respect to given constraints represented as sketches [4], images [5] or depth maps [6]. On the other hand, several researches have attempted to combine cross-class objects by structure similarity [7] or a given guidance shape [8]. However, in these methods, the unknown function of the parts limits the forms of the synthesized models into fixed structures, and the constraints focus on the appearance of the parts rather than their affordance.

In the past few years, leveraging ergonomics to study the human-object relationships has become a hot research topic with various attentions proposed in the literature. For example, the guideline defined by following the ergonomics enables the use of a human pose to explore proper man-made objects which have certain parts associated with human body, and inspire the reshaping of these models [9]. This motivates us to use one or multiple human poses to facilitate shape synthesis. Compared to reshaping, shape synthesis allows more interesting shape variations by properly assembling parts instead of simply deforming them. Such advantages are more obvious for the design of functional hybrids.

Functional hybrids, which are designed with multiple functional components from different shape categories or for multiple operators, are very interesting and have practical applications in the real world. For instance, as shown



Fig. 1. Composite designs with in-class combination for multiple operators (a & c), and functional hybrids with multi-function components (b & d).

in Figure 1, the Tandem Bicycle is popular with couples (Figure 1 (a)), and a Taga Bike, which contains the functions of both bicycle and stroller assists mothers in conveniently taking their babies for outdoor activities (Figure 1 (b)). However, since such designs have more creative structures, it is always challenging for the recent shape synthesis methods. A key problem of the functional hybrid design is the vague correspondence of the parts when dealing with shapes across different categories. The novel structures also make it hard to collect enough examples for shape synthesis via statistical methods. We observe that a human pose might be a bridge between shapes from different categories, especially for the designs used by a single operator. For example, the design of Taga Bike is mainly because of the similar postures of upper limb needed for using bicycle and stroller.

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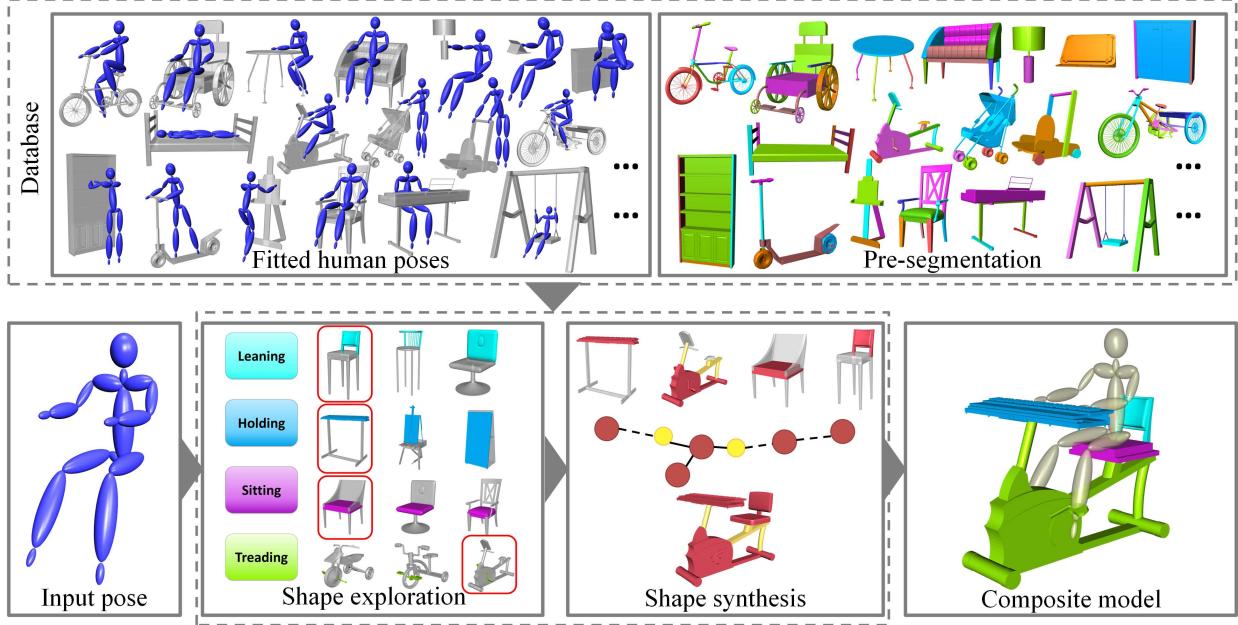


Fig. 2. An overview of our approach. With a pre-segmented database and associated human poses, our system explored proper shapes from one or multiple categories to satisfy the input pose, and assemble their components into a model with well-connected structure.

With this observation, we propose a pose-inspired approach for shape synthesis and designing functional hybrids. Given the availability of easy-to-use interaction paradigms (e.g., based on Inverse Kinematics) for editing human poses, we intend to make even novice users get inspirations for possible functional hybrid composite objects by simply manipulating human poses. To achieve this goal, we first derive the pose prior from a database where each model has been pre-segmented and fitted with a posed human skeleton. Such a prior lets the edited pose provide components for potential in-class or cross-class assembly. To insure the rationality of synthesized models, we also compute category compatibility between different categories via a user study. Given an input human pose, our approach uses such a pose and category priors for suggesting group shapes, which provide components and potential connecting relations for composite synthesis. Our approach also supports user control over the suggestion process by explicitly specifying desired object categories, and enables the design of functional hybrids for multiple associated human operators.

The main contribution of this work is a unified framework to leverage a human pose to explore object parts with proper affordance from four typical affordance types, and to enable in-class and cross-class shape synthesis and functional hybrid creation. We show the effectiveness of our approach by generating synthesized models from 18 classes of objects, leading to various interesting, nontrivial functional hybrids. We evaluate the usability of our approach by comparing to a state-of-the-art part-based modeling technique [10], which, like ours, also supports the synthesis of both in-class and cross-class shape. We also compare our approach to a state-of-the-art ergonomics-inspired reshaping technique [9] to show that more interesting shape variations can be created via our system.

2 RELATED WORKS

In this section we first review the literature about the human factor in geometry modeling. Then we examine the relevant works on shape exploration and data-driven 3D creation.

Human-centric shape analysis. To exploit functional properties of different model categories, affordance analysis, which leverages the object-human interaction to detect the functionality of objects, has been actively studied in recent years. Grabner et al. [11] imagined an actor performing actions in one scene to recover the functions of the target objects. Saul et al. [12] proposed an interactive chair modeling approach for personal fabrication. Fouhey et al. [13] exploited the coupling between human actions and scene geometry for single-view 3D scene understanding. Chen et al. [14] proposed *PoseShop* to construct segmented human image database for personalized content synthesis. Kim et al. [15] proposed a novel analysis approach to predict a corresponding human pose from an input 3D model. Zheng et al. [9] introduced an ergonomics-driven system which links ergonomic considerations to shape exploration and reshaping. Moreover, such a human-centric idea has also been applied to 3D scenes analysis [16], [17], [18] to reveal the object-human and object-object interactive relationships, and applied to 3D scenes synthesis [19], [20], which leverages human action to inspire object arrangement and obtain more functionally-valid 3D scenes. Our work is based on the success of affordance analysis of individual objects, and proposes to use a human pose to build sparse correspondence between multiple shapes across different categories for composite design.

Shape retrieval and exploration. Exploring shapes from collection has been widely studied. Most of existing works (e.g., [21], [22], [23], [24], [25]) adopted low-level or part-level geometric/topological features, directly comput-

ed from shapes for shape description and comparison. Liu et al. [26] introduced an indirect shape analysis approach, which makes use of agent-object interactions for 3D shape retrieval. Our work is most related to theirs but with significant differences. First, their work focuses on describing a single shape with respect to multiple poses, in terms of pose fitness. In contrast, we care more about how multiple shapes can be fitted to a single pose. Second, the inputs (a single shape as query versus one or multiple poses) and outputs (the retrieved shapes most similar to the input query versus composite models synthesized with respect to the input poses) are completely different.

Data-driven 3D creation. Modeling by assembling existing shape components extracted from a database has been a popular approach for shape synthesis. Part assembly has been used for open-ended shape synthesis [10], [27], structure recovery from depth scans [6], or interactive modeling [2], [28], possibly with sketch-based interfaces [4]. Most existing approaches support shape synthesis of in-class variations only. Shape synthesis with structure variations, which allow more interesting creations, is generally a challenging task for these works. For example, Alhashim et al. [29] proposed to synthesize shapes via topology-varying structural blending, which requires part-level shape correspondences. Since such correspondences are hard to be determined for shapes across different categories, their method is more suitable for in-class shape synthesis. On the other hand, Lun et al. [30] proposed to transfer the geometric style of man-made objects across different shape categories with their original functionalities preserved. Since their work focuses on the geometric properties of shapes, the functional hybrid creation which always needs structure variations remains challenging. The work of [7] is exceptional and supports both in-class and cross-class shape synthesis. However, their work is for open-ended modeling. In short, although the existing methods are able to generate many interesting shape variations, none of them can be easily adapted to design functional hybrids with respect to given input poses, which provide a completely new user interface and metaphor to control the assembly process.

3 OVERVIEW

As illustrated in Figure 2, we aim at a framework that leverages a given human pose to inspire the design of interesting functional hybrids. This is achieved by using the knowledge of a database of pose-model pairs. Our models in the database cover multiple categories of objects, making the resulting composites original and interesting. In the pre-processing step, each model was fitted with a human pose [15]. All the models were also pre-segmented into semantically meaningful components using the state-of-the-art, user-assisted geometry segmentation methods [31], [32]. With the fitted pose for each model, we can establish sparse correspondences between the parts related to human body from different models.

We focus on four types of human-object affordances, namely, leaning, holding, sitting and treading. These interactions involve different part(s) of human body, which is represented by a skeleton with 19 bones. The poses of

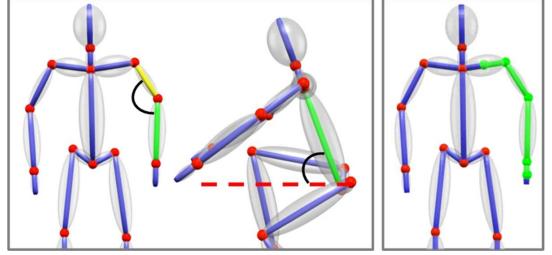


Fig. 3. **Left:** The posture parameters based on joint angles. **Right:** The path (in green) between hand and shoulder. We use such paths to calculate the distance between two bones.

each affordance type can indicate the configurations of the parts with the same semantics, and even the categories of the parts with different semantics. For example, a deck chair and a bar chair have different backrests due to the different poses using these chairs, and the poses are different using bicycle handlebars and chair armrests likewise. On this basis, we relate the interactive parts of 3D shapes to the affordance types. Thus even the parts of the shapes across different categories can be exchangeable as long as they have the same affordance type, while the human poses can be used as descriptors to differentiate such parts. These observations motivated us to leverage an input human pose to facilitate the synthesis and functional hybrid of both in-class and cross-class 3D shapes.

Figure 2 gives an overview of our framework. Given a human pose, our approach first explores a group of shapes that provide certain components which well fit the input pose with respect to certain types of human-object interactions (Section 4.1). Then we employ a graph-based structure combination algorithm to combine these components with proper connecting relations to form the structures of the synthesized models (Section 4.2). In this manner, our approach enables the synthesis of both the in-class and cross-class objects. Moreover, the synthesized models which are originally designed for a single operator with a single pose, can be used for further composition to create models for a single operator with different poses and for multiple associated operators via the graph-based structure combination algorithm. We provide a tool that assists users in designing the above two kinds of synthesized models (see also supporting information video demo). Since the input human pose can be obtained by editing the skeleton based on Inverse Kinematics or from other ways such as image-based pose estimation, our tool is convenient for users even novices.

4 METHODOLOGY

4.1 Pose-Inspired Object

As mentioned above, we choose a human pose as a descriptor to explore shapes for synthesis and functional hybrid. To this end, we collect a database of pre-segmented models with posed human agents. The parts which are in contact with the human body or the ground are then labeled to obtain the human-object pose prior. Hence, given a user-specified human pose, objects with the proper interactive parts can be explored from one or multiple shape categories.



Fig. 4. The locus of each type of human-object affordance on a skeleton (left), and examples of interactive parts which are labeled by the contacting locus bones (right).



Fig. 5. Given a human pose (left), we show the candidate shape selection and group selection (in red box).

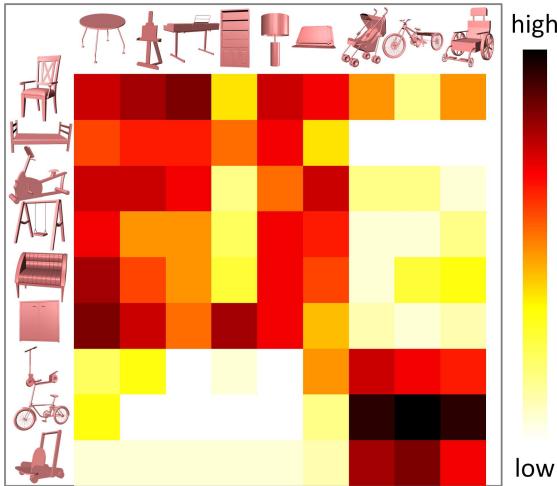


Fig. 6. Compatibility score matrix (partial) across different categories, obtained via a user study.

Human pose. Let $\{\mathcal{S}_1, \dots, \mathcal{S}_K\}$ denote a database of K models, each of them being associated with a fitted human pose [15]. These models are from 18 different categories, and the front orientations of all models in the same category are aligned by aligning their associated human poses to a use-specified reference pose. We represent a human pose using a simplified human skeleton consisting of 19 bones $\{\mathcal{B}_1, \dots, \mathcal{B}_{19}\}$, and use the joint angle, i.e., the included angle between one bone and its parent bone as a posture parameter (see Figure 3 (left)). Note that we choose the spine as the root bone, whose parameter is the included angle between the spine and the global forward orientation. In this way, we obtain a 19-dimensional vector \mathbf{x} as the pose feature.

For each of the four affordances types (i.e., leaning, holding, sitting and treading), we identify certain bone(s) as the *locus* of affordance, denoted as $\{\tilde{\mathcal{B}}_1, \dots, \tilde{\mathcal{B}}_4\}$ (Figure 4 (left)). For example, the spine is the locus of leaning and the hip is the locus of sitting. The shape parts which are in contact with such bones are labeled by these bones. We call such parts as the *interactive parts* (Figure 4 (right)). Besides, assuming that our shape has a known upright orientation [33], we also identify the *base parts* (e.g., the legs of a chair, the wheels of a bike etc.) of a shape as those touching the bottom face (the ground) of the bounding box of the shape. Thus, we establish sparse correspondence between interactive parts among all shape categories.

Our next goal is to suggest groups of shapes, whose members provide certain interactive parts which are combinable and meanwhile locally fit for the input pose. Exhaustively searching for all possible combinations of shapes in the database is computationally prohibitive. As illustrated in Figure 5, we take a two-step approximation approach: candidate shape selection and group selection. The first step ranks all repository models based on the pose similarity for each type of affordance, leading to four ranked lists of shapes. We keep only the top- K ranked shapes in each list. The next step of group selection identifies possible combinations of shapes from different ranked lists in terms of pose similarity, category and user intention.

Candidate shape selection. The purpose of this step is to quickly filter out most of the shapes highly irrelevant to the input pose so that the time complexity of group selection is still manageable. Let \mathbf{x}_o be the feature of the input pose p_o and \mathbf{x}_k be the posture feature of the k -th model with pose p_k in the database. For the j -th affordance type whose locus bone is $\tilde{\mathcal{B}}_j$, assume $P_o(\tilde{\mathcal{B}}_j)$ is the relative position of $\tilde{\mathcal{B}}_j$ to the root bone of pose p_o , and $P_k(\tilde{\mathcal{B}}_j)$ is introduced similarly for pose p_k . We calculate the distance between the related locus bones' positions of the two poses, and the weighted distance of the two posture features to measure the similarity of the poses as follows:

$$D(p_o, p_k, j) = \|P_o(\tilde{\mathcal{B}}_j) - P_k(\tilde{\mathcal{B}}_j)\|_2^2 + \sum_{i=1}^{19} |\omega_i \cdot (\mathbf{x}_o(i) - \mathbf{x}_k(i))\|_2^2, \quad (1)$$

where $\omega_i = \frac{\omega'_i}{\sum_i \omega'_i}$ is a normalized weight for each bone \mathcal{B}_i . ω'_i accounts for the influence of the current affordance type of interest. Specifically $\omega'_i = \exp(-d(\mathcal{B}_i, \tilde{\mathcal{B}}_j))$, where $d(\mathcal{B}_i, \tilde{\mathcal{B}}_j)$ is the node-node distance between \mathcal{B}_i and $\tilde{\mathcal{B}}_j$.

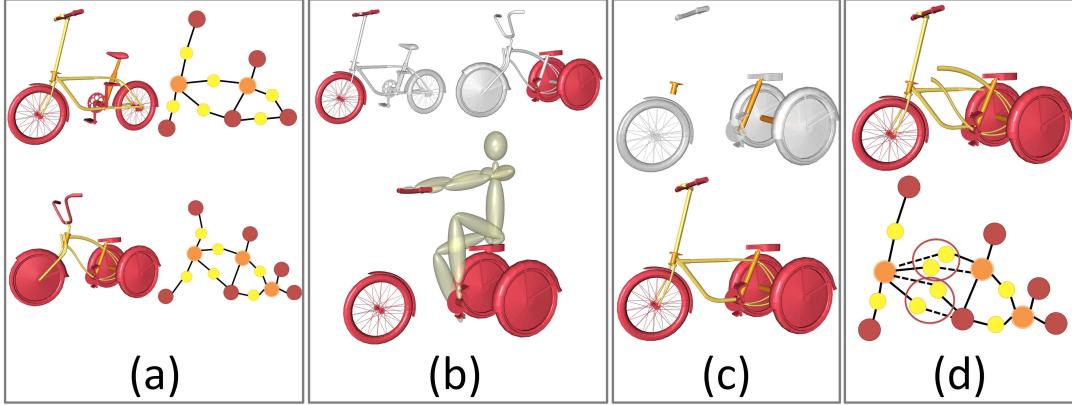


Fig. 7. (a) two shapes with their relation graphs. The functional, relay and link nodes are highlighted in red, orange and yellow, respectively. (b) the selected functional parts are placed based on the given agent. (c) the relay nodes are selected by the nearest functional nodes (top), and then the link nodes are selected to complete the structure by and connecting the nearest nodes (bottom). (d) we show how we select the link nodes from the conflicting ones (bottom in red circle). Note that the selected ones are easier to connect the nearest node with smaller distortion (top).

in the skeleton graph (Figure 3 (right)). That is, when \mathcal{B}_i is farther away from \mathcal{B}_j , \mathcal{B}_i plays a less important role in calculating the pose distance. As a consequence, some shapes whose associated postures are partially similar to the input pose can also be suggested. Then we use the above weighted distance to rank all repository models for each type of affordance with respect to the input pose, leading to four ranked lists. Since the objects from all shape categories are mixed together in each rank list, one category could have too many proper objects with precedence orders. To encourage more categories to participate in the synthesis, we limit the maximum number of the suggested objects in the same category to 3 in each ranked list (Figure 5). Note that our user interface allows users to specify desired categories. To give higher priority to the exploration of objects from these user-specified categories, we increase the distance of other categories as $\tilde{D}(p_k, p_o, j) = D(p_k, p_o, j) + W$, where $W = \max(D(p_k, p_o, j))$, $\forall k$. This is a hard constraint to insure the user-specified categories to participate in the next group selection. Besides, if the user chooses only one shape category for the in-class synthesis, all objects in the user-specified shape category are considered for ranking.

Group selection. Each candidate group contains one shape from each ranked list for each affordance type. Let $\mathcal{G}_m = \{\mathcal{S}_{m_1}, \dots, \mathcal{S}_{m_4}\}$ denote such a group. Note that some of the group members might be the same, since a single shape (e.g., a chair) might provide multiple types of affordance (e.g., leaning and sitting). Directly using all objects in the rank lists can lead to combinatorial explosion. Consider the objects with precedence orders are more likely to suit for the input pose, we use only the top-9 objects in each ranked list to generate the candidate groups. Since we have limited the maximum number of the objects in the same category to 3 in each ranked list, this step can insure 3 to 9 shape categories to be explored for each ranked list. In this manner, we simply use an exhaustive approach to identify groups of shapes (i.e., out of 9^4 all possible combinations) for shape synthesis.

The main challenge here is to define a proper metric to evaluate the quality of a candidate group. We found

that the following criteria generally work well. First, the pose associated with each shape should match the input pose. Second, the combination of the involved categories should be reasonable. Lastly, user-desired categories should be respected. To quantify the last two criteria we associate a binary vector \mathbf{y}_m with a candidate group \mathcal{G}_m , where \mathbf{y}_m has K components (K is the total number of categories in the database; $K = 18$ in our case) to represent the involved categories. That is, the n -th component $\mathbf{y}_m(n) = 1$ if \mathcal{G}_m contains a shape of the n -th category, and 0 otherwise. Let $\{p_{m_1}, \dots, p_{m_4}\}$ denote the poses associated with $\{\mathcal{S}_{m_1}, \dots, \mathcal{S}_{m_4}\}$ and p_o the input pose. We use the following metric to quantitatively evaluate the quality of \mathcal{G}_m :

$$E(\mathcal{G}_m) = E_1(p_o, \mathcal{G}_m) + \beta E_2(\mathbf{y}_m) + \gamma E_3(\mathbf{y}_m, C), \quad (2)$$

where we always use the weights $\beta = 10$ and $\gamma = 0.1$ in our experiments, and the three terms are defined as follows:

$$\begin{aligned} E_1(p_o, \mathcal{G}_m) &= \sum_{j=1}^4 D(p_o, p_{m_j}, j), \\ E_2(\mathbf{y}_m) &= \sum_{i,j} A(i, j) \cdot \mathbf{y}_m(i) \cdot \mathbf{y}_m(j), \\ E_3(\mathbf{y}_m, C) &= \lambda \|\mathbf{y}_m\|_0 + \sum_{c \in C} \|\mathbf{y}_m(c) - 1\|_2^2. \end{aligned} \quad (3)$$

The first term $E_1(p_o, \mathcal{G}_m)$ is the sum of the weighted pose distances of each member shape in the group \mathcal{G}_m , with the distance function $D(p_o, p_{m_j}, j)$ defined in Equation (1).

The second term $E_2(\mathbf{y}_m)$ is the energy with the category prior $A(i, j)$, which indicates how likely the two categories i and j can be combined. Not all combinations of categories would lead to semantically meaningful results. For instance, it is not very reasonable to combine a bicycle and a bed as a practical composite model. Automatically determining whether two categories are semantically combinable is a challenging task on its own. Instead, we resorted to a user study to obtain the category prior. Specifically, the user study was conducted with 20 participants, all graduate students of computer science. We asked each participant to evaluate the rationality of combining individual category

pairs, which were presented in a random order, and to give a score in the range from 0 (least reasonable) to 100 (most reasonable). Let $a(i, j)$ denote the average score for the i -th and j -th categories (see Figure 6). Then the category prior is computed as $A(i, j) = (1 + a(i, j))^{-1}$.

The last term $E_3(\mathbf{y}_m, C)$ is the energy for user control over the suggestion process. The user may specify one or more specific category(-ies) to participate in the composite design in order to get user-desired results. Here, C is a set of user-specified categories. Note this term is a soft constraint in order to balance the impacts of the posture and specified categories both given by the users. We expect the L_0 norm of \mathbf{y}_m is big to encourage the participation of different categories in the composite design, and we thus use the weight $\lambda = -0.1$. Reversely, if λ has a positive value (e.g., $\lambda = 0.1$), it would encourage shapes from the same category to participate in the synthesis. In our experiments (Section 6) we will also show the in-class shape synthesis results. With Equation (2), we assess the quality of each possible combination of shapes from the four ranked lists and keep top groups with the lowest values of $E(\mathcal{G}_m)$ as the selected object groups for the next step of shape synthesis. Theoretically, the time complexity of the object exploration algorithm is $O(n^4)$, where n is the number of the selected candidate shapes. Since we have limited the maximum number of the suggested objects in the same category, the number of the candidate object combinations will not be too large, thus allowing a quick feedback in this stage. The explored object groups are displayed in our user interface for users to choose. Since different explored object groups may have the same objects with respect to the same type of affordance, we remove the duplicate objects under each type of affordance to clear our user interface.

4.2 Shape Synthesis via Graph-Based Combination

The objects in the selected group provide parts with respect to their affordance type for shape synthesis. However, only the interactive parts are not enough to form functionally-valid and visually-pleasing synthesized models. This is because the synthesized models, especially the functional hybrids with components from different shape categories, could have completely new structures. Hence our goal in this stage is to use the components and potential from each suggested objects and merge these components into a complete, well-connected structure of the synthesized shape. To this end, we use the relation graph to represent the structure of the shape, and employ a graph-based combination algorithm to form a whole model by merging the divided components.

Structure representation. The structure of a shape is represented using a *relation graph*, with nodes representing pre-segmented shape parts and edges encoding the adjacent relation between parts. Namely, if two parts have connected or overlapping regions, an edge is set to link their representing nodes in the relation graph. Note that in our relation graph, if the connect point of two parts is on the third part, we do not preserve such an edge since it can be replaced by the connecting relation of the two parts to the third part. In this way, the relation graph only contains the basic connecting relations.

In the resulting relation graph, a shape contains several components to link the functional nodes (i.e., interactive or base parts) together. We intend to discover the roles of these components to facilitate structure combination. For a part in the relation graph represented by node n_i , it might have two or more neighbors, denoted as $\{n_j^l\}$. We classify the nodes with two neighbors as the *link nodes*, which play a role to connect two parts, and the nodes with more than two neighbors as the *relay nodes*, which play a role to be connected. In this manner, a shape structure can be represented by several functional and relay nodes as well as several link nodes to connect them, as illustrated in Figure 7 (a).

Structure combination. At the stage of object exploration, some interactive parts have already been provided, and our system has a user interface (Section 5) that assists users in selecting certain base parts to participate in the composition. However, the other components and their potential connecting relations in the new structure are undetermined. To address this problem, we perform a structure combination algorithm to select the proper relay and link nodes, and find the proper connections to create visually-pleasing synthesized models. In this algorithm, since the selected objects for combination have been aligned with the input human agent, the positions of the functional nodes are determined. Then we leverage their positions to find the non-overlapping relay nodes $\{n_j^r\}$ based on the cost $RCost(n_j^r)$, which will be introduced shortly. After that, the neighbors of these determined nodes are selected and used to connect these existing nodes. Finally, we detect the overlapping link nodes and remove the one with larger deformation cost $LCost(n_k^l)$ to clean the models. The pseudo code of the graph-based combination algorithm is provided as follows:

Algorithm 1: Structure Combination

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Input: functional node set  $N^f$ , relay node set  $N^r$  and
link node set  $N^l$  in each object
Output: merged structure  $G = (N, E)$ 
 $N = N^f; E = \emptyset;$ 
 $\forall n_j^r \in N^r, j = 1, \dots, J;$ 
for  $j = 1; j \leq J$  do
  if  $\#n_j^r \in N^r$  overlapped with  $n_j^r$   $\| RCost(n_j^r) <$ 
   $RCost(n_{j'}^r), \forall n_{j'}^r \in N^r$  overlapped with  $n_j^r$  then
     $| N = N \cup n_j^r;$ 
  end
end
for  $k = 1; k \leq K$  do
   $\forall n_k^l \in N^l, k = 1 \dots, K, n_k^l$  is the neighbor of node
   $n_k \in N$  and can be connected to the node  $n_{k'} \in N$ ;
  for  $k = 1; k \leq K$  do
    if  $\#n_k^l \in N^l$  overlapped with  $n_k^l$   $\| LCost(n_k^l) <$ 
     $LCost(n_{k'}^l), \forall n_{k'}^l \in N^l$  overlapped with  $n_k^l$  then
       $| N = N \cup n_k^l;$ 
       $| E = E \cup e(n_k, n_k^l) \cup e(n_{k'}, n_k^l);$ 
    end
  end
return  $G = (N, E);$ 

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If the graph of the combined structure is still discon-

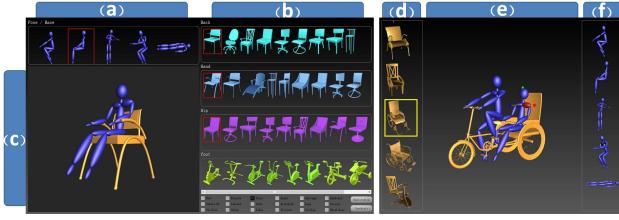


Fig. 8. User interface of our system with the single-operator design panel (left) and further design panel (right).

nected after the above step, we directly connect the nearest functional parts to ensure the connectivity of the graph. For example, the backrest and the seat of a chair are directly connected, rather than linked by a link part. In our implementation, the overlapping nodes are detected by the oriented bounding boxes of their representing parts. The cost $RCost(n_j^r)$ is defined as $\sum_{m=1}^M \|P(\tilde{n}_m^f) - P(n_m^f)\|_2^2$, where $\{\tilde{n}_m^f\}$ and $\{n_m^f\}$ are the top- M (we empirically choose $M = 2$) nearest functional nodes to relay node n_j^r in the original and synthesized shapes, respectively. The deformation cost of the link node n_k^l is defined as $LCost(n_k^l) = \|\tilde{n}_k \tilde{n}_{k'} - n_k n_{k'}\|_2^2$, where $(\tilde{n}_k, \tilde{n}_{k'})$ and $(n_k, n_{k'})$ are the two node pairs to be connected with n_k^l in the original and synthesized shapes, respectively. This algorithm has a time complexity of $O(J + K)$, where J and K are the numbers of the relay and link nodes, respectively, to obtain the preserved components and their relation graph.

With the structure completed, we then update the positions of all nodes based on the new connecting relations. In particular, the positions of the functional nodes are determined by the given pose, and the relay and link nodes are determined by preserving the relative distance between the node N to its j -th neighbor N_j . Namely, assuming the $P(N)$ and $P'(N)$ are the positions of N in the respective new and original structures, we calculate $P(N)$ by solving a least-squares optimization $\arg \min_{P(N)} \sum_j \|P(N) - P(N_j) - P'(N) + P'(N_j)\|_2^2$. Note we first choose the top- M nearest functional nodes as the neighbors of each relay node for the calculation, and then choose the two connected nodes as the neighbors of each link node. The positions of all nodes are also the positions of all parts' centres. Besides, to well link the neighboring parts of each link node part, we deform the link node parts (i.e., rotations and scalings) taking the same strategy as the method of Fu et al. [34], which uses the contacts (in terms of 3D points) of each part as the constraints to enforce the contact relations. Our system also allows users to adjust the composite models via editing the human pose following some ergonomics guidelines of Zheng et al. [9]. For instance, the orientation of the chair's backrest is related to the orientation of the human spine, and the width of the bicycle's handlebar is related to distance between two hands.

In this way, we obtain the composite model designed for a single human operator. Note that such a synthesis method is applicable to both the in-class and cross-class components. Our approach also allows composite design for an agent with multiple poses and for multiple human operators (e.g., examples in Figure 11). In these scenarios,

some parts in the designed models might be removed, e.g., adding a new interactive part to a designed model or choosing the base parts to combine two designed models. Then we use the approach described previously to generate complete structures and create the synthesized models (see our experiment in Section 6).

5 USER INTERFACE

We provide a user interface to assist users to explicitly control the synthesis results. Our user interface only requires a small amount of user inputs, mainly for editing the pose of human agent. To control the synthesis results, users may also assign their desired shape categories during the exploration stage (Section 4.1), and/or select the explored objects to provide their interactive or base parts during the synthesis stage (Section 4.2). Our interactive tool consists of two panels: the first one enables object exploration and shape synthesis for single-operator designs; the second one collects the designed single-operator designs and supports further designs, i.e., single operator with multiple poses and multi-operator designs. Below we give more details.

As illustrated in Figure 8, in the panel for single-operator designs, users first select a human skeleton with one of the preset poses to reduce the efforts for creating a rough pose (a). Then the skeleton can be adjusted to a user-desired pose for object exploration (b). After that, series of candidate objects with respect to different types of affordance are suggested for user selection (c). Note that four types of affordance are considered in our implementation, and the same objects could provide different interactive parts and be explored in different candidate series. Finally, four or fewer candidate objects from different exploration series are selected to provide their interactive parts for shape synthesis. Users also have to assign which object(s) provides the base parts for the final synthesized models. This process supports both in-class and cross-class variations, and automatically leads to new structures given cross-class candidate objects.

In the second panel, users can choose the models (d) generated by the first panel for the further design. These models are grouped based on the preset typical poses (f) of the agents which can be chosen by the users for manipulation (e). In this panel, users can manipulate the posture of the human agent associated with the selected model, and select the other model to add new functional part to the existing model. Users can also manipulate the positions of multiple human agents and choose the based parts to combine their associated models generating synthesized models for multiple human operators. Besides, the part configurations can be continuously edited in both two panels as long as the postures of the agents associated with the composite model are edited by the user.

6 EXPERIMENTS

In this section, we evaluate our approach on shape synthesis with various experiment results and comparisons with the state-of-the-art shape synthesis methods [9], [10]. The results produced by our technique include the in-class composition models, which have been widely studied, and also the functional hybrids, which are multi-function or designed

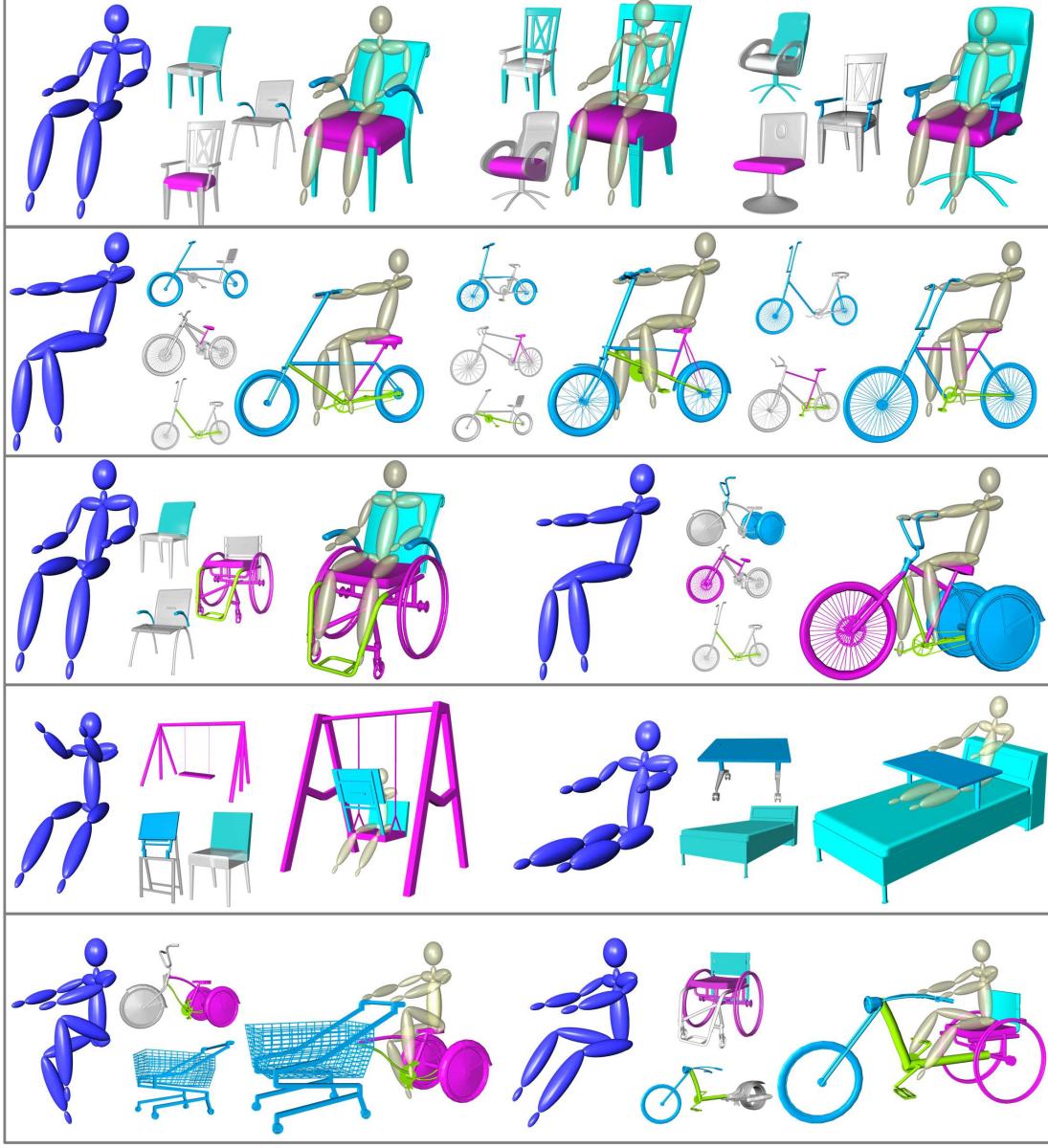


Fig. 9. Functional hybrids inspired by single input poses.

for multiple human operators. We show how the user can control the design process by manipulating the pose(s) and specifying one or more desired categories.

Shape synthesis. We collected a database consisting of 163 3D objects across 18 categories, including 20 chairs, 5 wheelchairs, 6 swings, 12 bicycles, 6 tricycles, 7 gym equipments, 9 beds, 12 tables, 8 trolleys, 5 strollers, 6 easels, 6 keyboards, 10 bookshelves, 10 cabinets, 11 lamps, 10 skateboards, 10 tablet PCs and 10 sofas. As mentioned in Section 3, each shape has been fitted with an appropriate human pose and segmented into meaningful pieces of parts. On average, the object exploration algorithm took about 3 seconds, and the structure combination algorithm took less than one second, all tested on a PC with Intel Core i7-4790 3.60GHz PC with 16GB RAM. Our system required an extra time cost (about 5 seconds) to refine the part connection of the synthesized model and to spend on the I/O stream. As

long as the structure and part connection are determined, the shape editing can be done in real time following the pose edited by the user. On the other hand, manual pose editing typically takes less than one minute for a single agent with our IK-based interface.

Figure 9 shows a set of composite models designed for a single human operator under various poses. In each case, we show the input pose, synthesis result and the selected group objects that provide the composable components. The top two rows of results were synthesized by recombining in-class shapes by constraining the algorithm on user-specified categories. We use the top-3 suggested object groups for the above results. With the input pose as the constrain, the in-class composition models exhibit interesting shape variations while respecting the given pose. The middle two results in the third row were synthesized by the shape categories with the similar functions but different configurations. These cases indicate that the number of

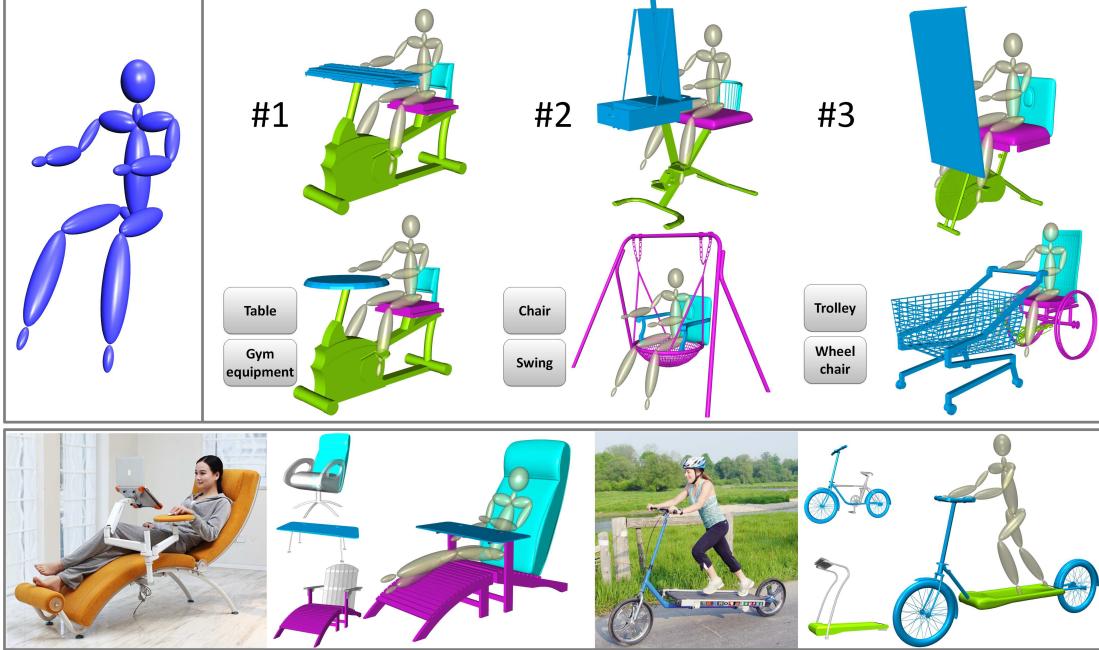


Fig. 10. **Top:** Given the same input pose, we show the synthesis results generated by the top-3 suggested object groups (right-top), and more various results with some user-specified categories (labeled in the textbox in the left of each case). **Bottom:** The poses extracted from images inspire the functional hybrid design via the exploration and synthesis by our method.

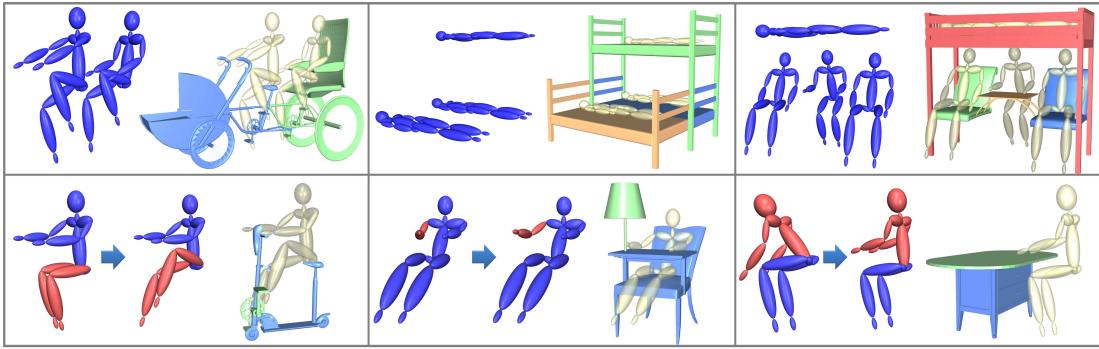


Fig. 11. **Top:** With our method, it is easy to design composite objects that are readily used by multiple human operators. Note the components belonging to different agents in different colors. **Bottom:** By editing the pose of a model (red part of the agent in each case), a new component (green) can be suggested to add to the existing model (blue), enabling multiple functional components with respect to the same affordance type can coexist in a single synthesized result.

shapes in some categories like tricycles and wheelchairs can be extended by bringing the components from the other categories via our approach. The bottom four results were synthesized by recombining multi-class shapes, which are functionally different.

In Figure 10 (top), given the human pose, which is the same one in Figure 5, we provide the composite models generated by the top-3 suggested object groups, and show how the user-specified categories impact the object exploration and generate various interesting synthesized models. Note that the user can choose fewer than four types of components for different affordance. For an example of the swing-chair result, when a swing is suggested, there is no need to choose the component for treading affordance, making only three objects used to provide the components. In Figure 10 (bottom), we only use the postures extracted from the images to inspire the functional hybrid creation by our method. The explored component shapes and the

synthesized models that are similar to the designs in the images, validate the practicability of our pose-to-design system.

The produced single-operator designs can be combined to synthesize more complex models for the same operator with multiple poses or for multiple operators. As illustrated in Figure 11, we show various further designs created by our system. The top three cases are synthesized by manipulating multiple operators to combine their associated shapes together. The bottom three cases show how to add new functional components to a model by adjusting the pose. For an example in Figure 11 (bottom-right), adjusting the pose (red parts of the agent) associated with a cabinet, leads to a tabletop adding to the cabinet, while the position of the tabletop follows the adjusted pose. In this way, the synthesized model has more than one kind of functional components with respect to the same affordance type.

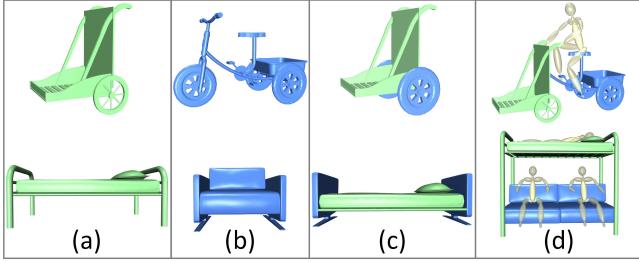


Fig. 12. Comparisons with [10]. In each row, (a) and (b) are input shapes for synthesis, (c) is the results of [10], (d) shows our results and the given poses.

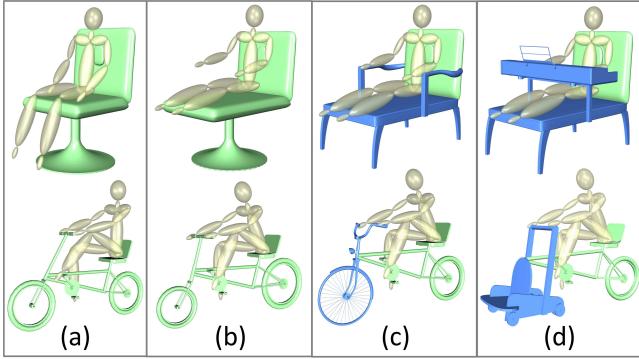


Fig. 13. Comparisons with [9]. In each row, (a) is the input shape and its associated pose, (b) is the edited pose and the reshaping result of [9], (c) and (d) are our in-class and cross-class shape synthesis results, respectively. The parts explored by our method are highlighted in blue.

Comparisons. We compared our approach with *smart variations* [10], which is one of the very few methods supporting both in-class and cross-class shape synthesis. Their approach is based on the extraction and combination of symmetry-driven sub-structures, called *sFarr*. As shown in Figure 12 (c), the approach of Zheng et al. is able to automatically synthesize interesting shape variations when the sub-structures, i.e., the special arrangements of parts, exist in both input models. However, their method is essentially open-ended and does not support explicit control over the desired design. In addition, it is impossible for their method to produce results like the one in Figure 12 (d-bottom), since such synthesis is already beyond the definition of *sFarr*.

We also compared our approach with ergonomics-inspired reshaping approach [9], which leverages the human pose to reshape the interactive objects based on the predefined ergonomics guidelines. As illustrated in Figure 13, we show the initial models and poses (a). After changing the pose edited, we show the reshaping results generated by the approach of Zheng et al. (b), the in-class and cross-class synthesis results of our approach (c and d). It can be seen that, with the human poses changed, our approach takes another strategy exploring more suitable components to replace the original ones, rather than always deforming the original parts which might lead to severe distortion. Moreover, such a strategy enables the exploration of the cross-category components for more interesting shape variations. Note that an initial model is not necessary for our approach.

As an alternative approach for producing functional hybrids, Hu et al. [18] proposed to use the functionality model

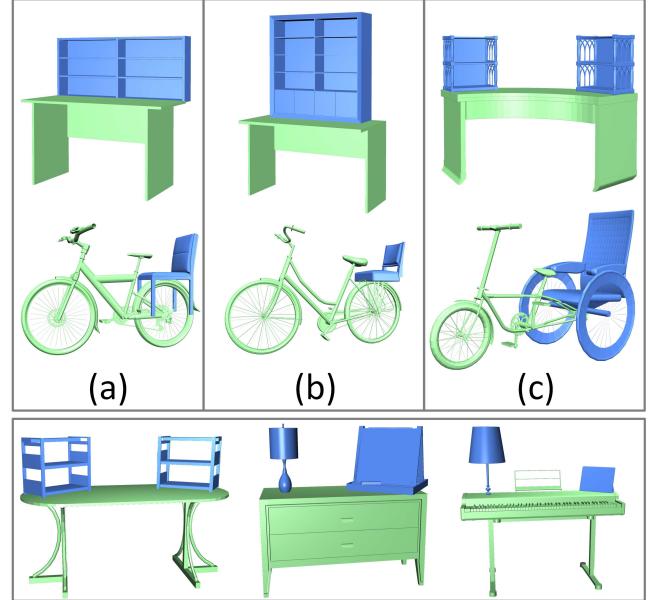


Fig. 14. **Top:** comparisons with [18]. (a) functional hybrids created by [18]. (b) similar results created by our system. (c) also our results but with complex structures which are challenging for [18]. Parts from different objects are separated by colors green and blue. **Bottom:** reusing the design of (c)-top to create more results by changing the added objects in each step (left), or even their categories (middle and right).

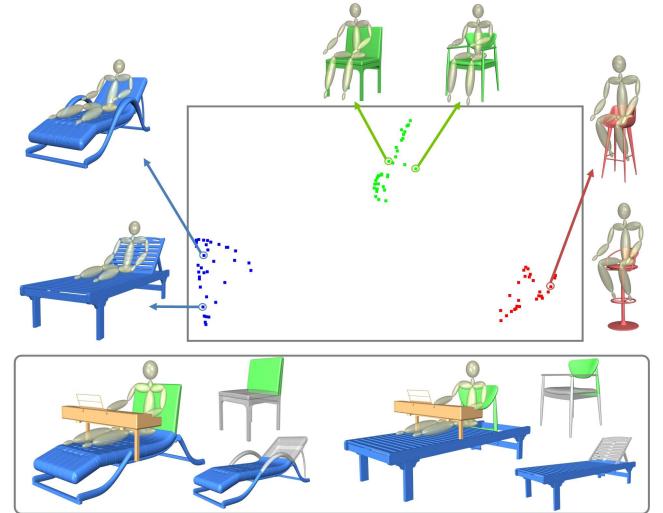


Fig. 15. **Top:** 100 chairs are clustered into 3 groups based on their pose features. We show two representative members with the associated poses in each group. **Bottom:** parts from the objects in the same group can be exchanged to generate more synthesized models.

for functional hybrid creation. We compare our results with theirs. In Figure 14 (top), we can see both the approaches can generate valid functional hybrids ((a) and (b)). Our system allows users to select the base parts to avoid the redundant parts (e.g., the chair's legs in (a)-bottom), and enables structure combination to create functional hybrids with complex structures (e.g., (c)-bottom) which are challenging for [18] where two shapes are directly attached together. Besides, since the method of [18] lacks an interaction mechanism, shapes like the one in (c)-top which have multiple components (two blue shelves) added in different ways could hardly be automatically created. Our system enables such

a creation by interactively editing the associated poses of the shapes, e.g., rotating the spine of the agent to change the posture facing direction in this case. In our system, such a design requires manual adjustment of the human pose. However, since the manual manipulation is applied to the human pose rather than the object, the same pose editing process of a design could be reused to create more synthesized models by changing the added objects or even their categories in each step, like the three cases in Figure 14 (bottom).

Extension to large-scale database. Since we limit the number of suggested models in each category, a large-scale database might not directly help increase the number of possible synthesized results. To address this problem, we use the pose feature (Section 4.1) to cluster the objects in the same category into a small number of groups. In each group, since the interactive parts have the similar configurations due to the similar postures, these parts can be used to replace the corresponding interactive parts in the designs to generate more variations. We conduct an experiment with a large chair database (100 models). The clustering result is illustrated in Figure 15 (top), where we show two representative models in each group to demonstrate their similar postures and configurations, and also show two synthesized models generated by part replacement (bottom) reusing the design in Figure 13 (d-top).

7 CONCLUSION

In this paper we have shown how to leverage the human pose to inspire shape synthesis, especially facilitating the functional hybrid creation. In particular, we proposed an approach to explore in-class or cross-class objects that provide proper components and connecting relations with respect to the input human pose, and combine them to a whole shape, which can be multi-function or for multiple operators. Such functional hybrids increase shape variations with the parts human-object correspondence established across different shape categories. The presented interactive system assists users in easily designing a shape that fits a certain pose or creating interesting functional hybrids.

Our current approach has several limitations. Firstly, like the previous works on assembly-based shape synthesis [10], [29], our approach relies on good-quality pre-segmentation of repository models. Poor-quality segmentation would cause unreasonable models. For an example in Figure 16 (top), the left case shows a well synthesized result when two input models in Figure 7 are well segmented. In the middle case, some parts in the frames of two input models are not segmented, leading to a different result. Although the frame is somewhat distorted, the result still looks plausible. In contrast, the frames of two input models are not segmented in the right case. To link the handlebar which is constrained by the input pose, the frame has to be severely distorted, causing a poor synthesized result. Besides, since the component selection step in our combination algorithm relies on overlap detection, a redundant part might not overlap with any existing parts if it connects two parts which are not necessary to be linked, and needs user intervention to remove it (Figure 16 (bottom-left)). Secondly, our approach

focuses on the functional hybrids based on the interactive parts that are associated with human body. This means the parts with object-object interactive functions cannot be handled by our system, while some related works (e.g., [18]) can address this problem and be integrated into our system. Moreover, since our approach aims to explore the proper components that are suitable for the input pose with respect to different types of affordance, the in-class shape synthesis designed for a single operator might not work for some categories like bed, table, etc., which do not have more than one type of affordance for composition. However, we can still use these shape categories to design synthesized models for multiple operators (e.g., Figure 11 (middle-top)).

Another limitation is that, the models for multiple operators in our system are designed by manipulating the associated human agents with user assistance. Although the structures can be automatically combined, it still needs users to handle the position or posture of each associated agent. For an example in Figure 16 (bottom-right)), to add a table between two chairs, the user needs to manipulate the agent (blue) associated to the table. Besides, in this case, two armrests of the chairs (purple) are functionally conflicting with the added table, it also needs user assistance to remove such redundant parts. Moreover, without user selection, our approach might also suggest redundant shapes. For an example in Figure 16 (bottom-middle), the fourth explored group provides a synthesized model by combining an easel with a tricycle. However, such two shape categories are functionally conflicting to make such a design not very practical to use. Fortunately, benefited from the category prior energy $E2$ in Equation (2), this scenario could only happen in the low-ranked explored groups.

In the future, we plan to further consider combining the ergonomics and structural functions of man-made shapes to improve the practicability of the design models. Moreover, we are also interested in embedding the cross-class objects into a space according to their associated poses, to enable continuous object exploration. We believe that using human-centric prior to inspire the model design can open up new opportunities towards the integrating functionality and provide a novel modeling paradigm which is more convenient for novice users to design models for the use of human beings.

8 ACKNOWLEDGEMENTS

We would like to thank the anonymous reviewers for their help in improving the paper. This work was partially supported by NSFC (61325011 & 61532003 & 61421003), the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. CityU113513, CityU11300615, CityU11237116), and the City University of Hong Kong.

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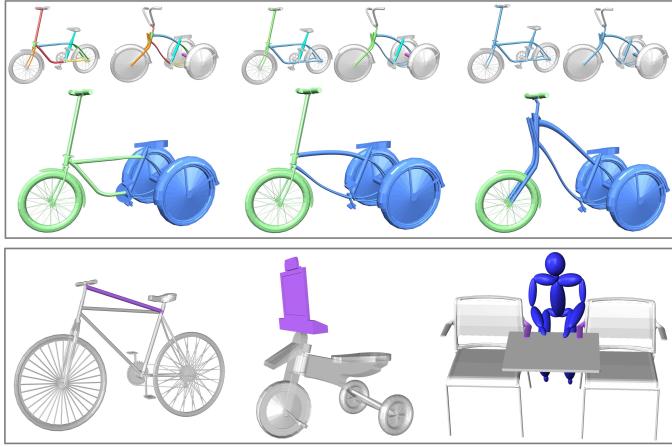


Fig. 16. Top: Shape synthesis results with different levels of pre-segmentation. Note the colored frames indicate segmented parts in each case (top) and the green parts of the synthesized results come from the input bicycle while the blue ones from the tricycle (bottom). **Bottom:** Failure examples with redundant or functionally conflict parts (highlighted in purple).

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