Towards a grasping-oriented categorization of rigid industrial objects to support automatic grasping of 3D CAD models in virtual ergonomics

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ABSTRACT
The use of automatic analysis of 3D CAD models to identify a variety of plausible grasp locations on unknown objects with complex shapes and no affordances is a current concern in virtual ergonomics. In robotics, researchers approached this problem by grouping objects into categories related to geometric characteristics. Category-level grasping approaches have been little explored in virtual ergonomics. This paper introduces grasping-oriented categorization for rigid industrial objects to support the identification of a variety of plausible grasp locations in virtual ergonomics. First, we performed a rough analysis of objects' convexity and define two high-level categories: *global dominant shapes* and *local dominant shapes*. Second, we propose a more detailed categorization of objects to sort them into four specific categories: 1- *threadlike objects*, 2- *thin objects*, 3- *small objects*, and 4- *large and thick objects*. Then, we explode those categories based on the presence or lack of *holes* or *protrusions that are useful for grasping*. This grasping-oriented categorization of objects is used to manually categorize a subset of 242 real rigid industrial objects. We obtained 27.3% *threadlike objects*, 43.8% *thin objects*, 2% *small objects*, 24.3% *large and thick objects* and 2.6% *uncategorized objects*. Our future work will pertain to develop approaches for automatically categorize unknown objects and approaches for automatically identifying variety of plausible grasp locations on objects of given categories in virtual ergonomics.

Keywords
CAD models, categorization, robotics, virtual ergonomics, grasp location, unknown objects, complex shape

1. INTRODUCTION
The simulation of industrial tasks that involve human interaction with objects can be done by generating interactions between a virtual mannequin and a computer-aided design (CAD) model of a query object. According to the object grasping research community, a query object can be classified as a known object, a familiar object, or an unknown object [27]. A known object is a query object that the automatic grasp generation engine has previously encountered, so the object's plausible grasp locations and grasp configuration are already known. Familiar objects are query objects that have not been previously encountered but whose shape is found to be similar to a previously encountered object. Unknown objects are query objects that have not been encountered before and whose shape cannot be matched with a previously encountered shape.

When it comes to approaches used to automatically generate human-like grasps for known and familiar objects in robotics and virtual ergonomics, some approaches are built on the paradigm of coupling the recognition of objects in an experimental database of known objects with the use of a database of pre-recorded human-like grasps [17]. There are also approaches built on the paradigm of transferring a representation of a pre-recorded human-like grasp for a given reference object to an object that is found to be similar to the reference object [27, 33]. As for grasping unknown objects, there exist approaches that rely on using pre-recorded grasp databases and intelligent approaches that attempt to automatically generate grasps without relying on the transposition of a pre-recorded grasp [7].

In the context of virtual ergonomics, the main limitation of those approaches is the need to use a vast grasp database, even for machine learning (ML) [30].

Construction of a 3D model database of industrial objects with real or synthetic grasps remains a major challenge for manufacturers. This is due to the wide variety of not only parts that need to be manipulated in manufacturing environments, but also possible grasp locations, and possible human-like grasp configurations [35]. For example, Pernot *et al*. (2015) noted that it is possible to have one million 3D CAD objects in the design of a submarine [34]. The manual annotation of potential grasp locations for ML would prove unpracticable for such a database. Moreover, intellectual property concerns would need to be addressed when building such a database of CAD models.

The industrial partner involved in that work has developed a technology for virtual ergonomics called the Smart Posturing Engine (SPE^{TM}). It is used to automatically position virtual mannequins in a 3D scene [3] and generate interactions with CAD models of various assemblies of objects. In its current form, it approximates an unknown object based on its oriented bounding box (OBB) and indicates if grasping is possible at the center of the six sides of the bounding box [3]. This does not always result in human-like grasps because such complex objects exhibit geometric irregularities that make the centers of the six sides of the OBB non-plausible grasp locations. Such traditional approaches are also insufficient in robotic grasping [5].

Some studies in the field of robotic support that “geometrically alike objects have similar graspable components and grasps should be designed with respect to the geometrical category of a given object” [25]. From there, one can derive heuristics to guide the identification of plausible grasp locations from object categories [43, 48]. According to Wen et al. (2021), the category-based grasp estimation approaches used in robotics are gradually proving themselves to be effective for everyday objects but have been little explored for industrial objects [44]. However, they seem to be useful for generalization in the context of grasping unknown objects as they can be used with both geometry-based and learning-based algorithms. In both types of algorithms, category-based approaches offer the advantage of enabling reasoning at a level beyond individual objects, by utilizing shared characteristics (e.g. thickness, cross-sections, curvatures) among objects within the same category [25]. Thus, category-level approaches have the potential to enhance the success rates of the SPE^{TM} by being integrated into both traditional geometry-based reasoning algorithms and learning-based methods. However, to the best of our knowledge, category-level approaches for grasping unknown objects remain relatively unexplored in virtual ergonomics, particularly for industrial objects.

Therefore, we hypothesize that the success rate of the SPE^{TM} in identifying a variety of plausible grasp locations on unknown objects can be improved by grouping industrial objects into categories according to their geometrical characteristics. We assume that the results of doing so will be useful to support the generation of human-like grasps for unknown objects without requiring pre-recorded object or pre-recorded human-like grasp databases. Our objective is therefore to propose a grasping-oriented categorization of industrial objects that will eventually allow to automatically identify a variety of plausible grasp locations on CAD models of unknown objects in virtual ergonomics. The consideration of the task to be performed, the automatic recognition of categories of unknown objects and the automatic identification of a variety of plausible grasp locations are all beyond the scope of this paper. However, the development of object categories allowed us to formulate hypotheses on object grasping by categories. These grasping hypotheses will be tested and validated in future work using experiments with human participants.

The remainder of this paper is organized as follows: Section 2 sets out the literature review of existing approaches used to categorize objects in CAD. Section 3 details the methodology. Section 4 presents parameters that affect the identification of graspable components or grasp locations on objects. Section 5 presents the proposed technique for grasping-oriented object categorization in CAD for virtual ergonomics applications and some examples of grasps that were manually generated with Catia V5’s Ergonomics Design and Analysis module. We then discuss grasping hypotheses related to our proposed grasping-oriented object categorization technique in Section 6. Section 7 concludes the paper.

2. STATE OF THE ART

Shape understanding in CAD requires both local and global analysis methods and is challenging because local methods (e.g., curvatures, cross-section shapes) do not integrate the global characteristics of shapes [11, 38]. Moreover, global methods (e.g., shape distributions, invariant moments, geometric ratios) lose information related to local characteristics [11, 38]. Therefore, some object categorization approaches in CAD rely solely on global analysis methods, and others, solely on local analysis methods. However, many CAD works refer to specific categories of objects without proposing global object categorization. Sun *et al.* (2018) and Pernot *et al.* (2015) focused on *thin parts* (which are also referred to as *flat components* and encompass *sheet parts*) and globally characterized them by their aspect ratio, which reflects very large lateral dimension measurements compared to the thickness of the object [34, 39]. Pernot *et al.* (2015) integrated local feature analysis and global analysis to identify *parts with thin* *features* [34]. These are parts that do not globally satisfy the aspect ratio constraint but have local regions that satisfy the aspect ratio constraint for thin parts. Putrayudanto *et al.* (2024) worked on decomposing *thin objects with relevant local features*, such as protrusions or openings lying on multiple faces [36]. Armstrong *et al.* (2008) and Lecallard *et al.* (2019) focused on *long slender objects* [1, 20]. This category relates to 3D objects for which one of the 3 dimensions dominates. Lai *et al.* (2022) considered *complex thin objects*, such as objects obtained by assembling a thin sheet with a long slender protrusion [19]. Geng *et al.* (2010) were interested in the subcategory of *thin objects* called *thin plates*, which are thin objects that have simple primitives as underlying surface, such as some *electromechanical components*, *laptops*, and *mobile phones* [12]. Goyal *et al.* (2012) studied the category of objects called *generalized sweeps*, which represent 3D objects associated with high-level shape definition parameters (e.g., radius, angle, width, geometric constraints). They are obtained by orthogonally sweeping a 2D profile along a trajectory represented by a 3D curve, with the geometry of the cross-section being variable or constant while the topology remains constant [13]. White *et al.* (2004) defined *multi-sweep volumes*, which are volumes composed of several sweeping sources that can follow various sweep paths in order to reach identical or different target faces [45].

More generally, object categories in CAD can be based on object functionalities, manufacturing processes, or geometric and topological meta-descriptions. For example, Manda *et al.* (2021) proposed the CADNET dataset with 43 object categories related to objects' functionalities and geometric attributes [29], such as *90 degrees elbows*, *bearing blocks*, *clips*, *contact switches*, *container like parts*, *cylindrical parts*, *flange like parts*, and *simple pipe*. However, it would be difficult to use these 43 categories to build heuristics for grasping objects. This is because of the high number of categories and the fact that there is no demonstrated direct link between an object's functionality and its plausible grasp locations. Ip *et al.* (2003) trained a KNN to be able to automatically classify industrial objects in CAD into four categories depending on their manufacturing processes: "*rotational parts, injection molded parts, cast-then-machined parts, and rotational-machined parts"* [15]. Sakurai *et al.* (1996) used geometric and topological meta-descriptions to differentiate *curved objects* from *polyhedral objects* [37]. Mortenson (2006) defined *simple CAD objects,* as those whose geometric construction does not use Boolean operations, and *complex 3D objects* otherwise [32]. This latter category can include *instances* (which are obtained by applying different scale transformations to primitive shapes along the axes), *parameterized solids*, *sweeps*, *solids generated by some form of nonlinear transformation*, or *solids generated by assemblies of primitives* using Boolean operations.

However, no systematic approach has been proposed that categorizes industrial objects based on their geometric and topological properties in order to support the automatic identification of a variety of plausible grasp locations in virtual ergonomics.

3. METHODOLOGY

Our overall framework for proposing and validating the grasping-oriented categorization of industrial objects for virtual ergonomics applications is as follows:

1- Literature review of existing techniques to identify plausible grasp locations by analyzing and understanding hand–object systems.
2- Proposal of a grasping-oriented approach to object categorization in CAD for virtual ergonomics applications.
3- Development of a dataset of 3D CAD models of confidential real industrial objects and a dataset of similar objects identified in the publicly available GrabCAD database.
4- Validation of the proposed grasping-oriented categorization method by manually categorizing objects from both datasets and determining the proportion of objects that are difficult to categorize. We then use the datasets to test hypotheses related to plausible grasp locations on objects in the grasping-oriented categories identified. This makes it possible to develop grasping hypotheses that represent basic heuristics relating sets of plausible grasp locations to the geometry of objects by category. For confidentiality reasons, only realistic objects from GrabCAD are presented for illustration purposes in this paper.
5- Discussion about the grasping hypotheses by analyzing possible hand configurations and hand configuration variability on objects' surfaces. This makes it possible to discuss plausible grasp locations on objects' surfaces by category.

We therefore reviewed related works published between 2015 and 2025 that were accessible in *Engineering Village* and *ScienceDirect*, and used the snowball effect. The English keywords used were: *human*, *grasp*, *grasping*, *locations*, *mechanisms*, *patterns*, *parameters*, *anthropomorphic*, *contact*, *model*, *manipulability*, *manipulation*, *dexterous*, *hand*, *motion*, *object*, and *interaction*.

Moreover, for each category, we should be able to describe hand configuration variability on objects' surfaces in terms of degree of freedom of translation and rotation on the surface of the object. These hand motion possibilities sustained the proposition of the grasping-oriented categorization. Moreover, they support the need for grasping hypothesis analysis after manually generating grasps and manually categorizing the objects in the real and realistic object datasets. To this end, we also rely on the mathematical definitions of curves, surfaces and solids used in CAD. More specifically, we classify geometric surfaces in accordance with the class invariance concept defined by Desrochers *et al.* (1994) [6]. For example, a spherical surface is characterized by the fact that the three rotations around the center leave the surface unchanged, whereas for a planar surface, translations following the axes on the plane and rotation around the normal to the plane leave the surface unchanged.

4. GRASPABLE PARTS AND HAND MOTION CHARACTERIZATION

The hand–object system highlights complex and uncertain interactions determined by a wide range of parameters, including hand parameters [4, 10, 21, 24, 31], hand–object manipulability measures [31], object surface curvatures [24, 31], object height and width normalized by the gripper or hand size [18], and direction of contact [26, 35]. Given the wide variety of parameters that affect the identification of graspable components or grasp locations in the literature, we have summarized in Table 1 the main parameters affecting hand configuration at grasp locations. These parameters are used to analyze and characterize plausible grasp locations on objects in order to group objects according to the similarity of their discrete graspable parts.

Feix *et al.* (2016) analyzed certain types of grasps by considering the *opposition between the thumb and the other fingers* or the *opposition of the thumb to hand palm* [10]. Przybylski *et al.* (2013) noted that several classic grasp types can be simplified by considering the thumb as a virtual finger and the other fingers as a second virtual finger placed on a face *opposite to the thumb* [35]. Lippiello (2015) analyzed the graspability of object regions using their *local curvatures* and found that concave regions are more favorable to stable grasping than flat or convex regions [24]. He noted that *finger size* is a critical factor when it comes to identifying plausible grasp locations. He also indicated that the possibility of placing a virtual finger at a *grasp location that is opposable to the position of the thumb* is linked to the *maximum aperture* an anthropomorphic hand can accommodate [24]. Feix *et al. (2014)* came to the conclusion that 96% of the objects handled in their experiments were held at a location where the *grasp aperture was less than* 7 cm, and in 83% of cases, *the grasp aperture was less than* 5 cm. They recommend using the latter value when designing robotic hands [8]. However, they considered only machinists and housekeepers in their experiments. Lee *et al.* (2014) conducted grasping experiments with a group of 50 students. They found that three-finger grasps are most often used for objects less than 4 cm wide and five-finger ones are used for objects 8 to 12 cm wide [21].

Parameter | Reference	[24]	[8]	[10]	[9]	[21]	[4]	[31]	[26]	[47]	[16]	[35]
Hand size	x		x		x	x	x				
Finger size	x					x	x				
Object local curvatures	x						x				x
Thumb position	x		x								
OBB dimensions		x			x						x
Major object axis		x									
Roundness around the major object axis		x		x							
Grasp type			x	x	x						
Contact map						x		x	x	x	
Finger manipulability measures							x				
Hand–object manipulability measures							x				
Hand approach direction								x			x
Object symmetry information											x

Table 1 Parameters affecting hand configuration at grasp locations

Brahmbhatt *et al.* (2019) identified correlations between object size, the number of fingers used for grasping, the use or non-use of fingertips, the use or non-use of the palm of the hand, and the use or non-use of bimodal grasping [4]. Bimodal grasping refers to grasping with two hands or two virtual fingers in contact with the object on opposable faces of the object. Thus, it is possible to establish a correlation between the area of the contact zone between the hand and the object and the total area of the object, which is called the *contact ratio* [47]. This could explain the parameters introduced by Kothari *et al.* (2018): the normalized dimensions of an object based on the dimensions of the robotic hand used to grasp it [18].

5. GRASPING-ORIENTED CATEGORIZATION

Our grasping-oriented approach to categorizing objects includes a first high-level categorization step and a second more detailed one. The first step is done to roughly estimate whether or not hand configuration on an object's surface can be determined from the object's global shape or local features. If the hand configuration on the object is mostly determined by its global shape rather than local features, the variation in plausible grasp locations on the object's surface will not be significant. We then propose a detailed categorization method that relies on specific object attributes that can lead to different hand configurations at different grasp locations. Also, we determine when an object has holes or protrusions whose dimensions permit them to be used to grasp the object (e.g., passing the hand through the hole, using opposable faces of a protrusion). Figure 1 presents our overall proposed grasping-oriented categorization approach for industrial objects in virtual ergonomics application.

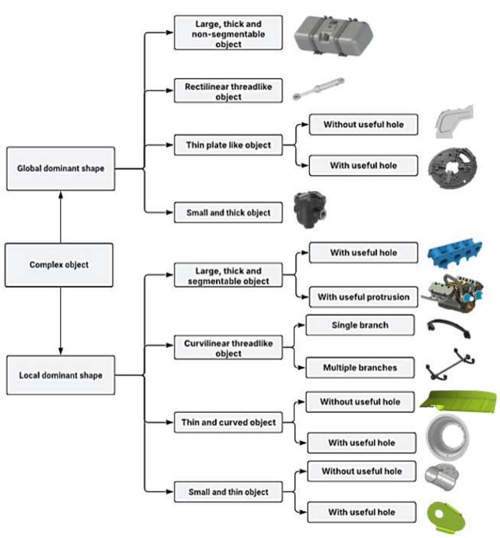


Figure 1 Grasping-oriented categorization of rigid industrial objects

High level categories: global dominant shape and local dominant shape

First of all, Feix *et al.* (2014) noted the difficulty of analyzing grasping on objects whose overall shape is complex. They linked the concept of grasp location to the local description of objects and the convexity of objects' components [8]. The 16 categories they proposed are specific to the intrinsic characteristics of the grasp locations and not relative to the global shape of the objects themselves. They essentially consider the representativeness of the three major axes of grasp locations and the properties of their cross-sections. The authors therefore introduced a distinction between identifying grasping possibilities from the global geometry of an object and identifying them from a set of local geometries on an object's surface. They noted, however, that their categorization approach is suited mainly to objects with affordance (designed with the intention of human interaction through grasping). Our study intends to categorize industrial objects that have been designed without affordance, or without any intention of interaction with humans.

Therefore, to move towards an analysis that combines local and global geometry analysis, we first define a *global dominant shape* as a 3D shape whose oriented bounding box is a good approximation of the object. We then extend this definition to other geometric primitive shapes (cylinders, spherical primitives, etc.) by redefining a *global dominant shape* as any shape whose Zunic and Rosin convexity [23] value is very close to 1. Zunic and Rosin convexity is defined as the ratio of the volume of the object to the volume of its convex hull. In contrast, the closer a geometric shape's Zunic and Rosin convexity value is to 0 (meaning the difference between the volume of the object and the volume of its convex hull is large), the more likely the shape is to have local features and thus belong to the *local dominant shape* category. Figure 2 below provides examples of *global dominant shapes* and *local dominant shapes* with their Zunic and Rosin convexity (c_{Z-R}) values. As an initial approximation, all shapes with $0 \leq c_{Z-R} \leq 0.5$ are *local dominant shapes*. The experimental identification of the exact threshold value is beyond the scope of this paper.

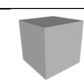
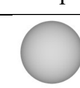
Global dominant shapes	 $c_{Z-R} = 1$	 $c_{Z-R} = 1$
	 $c_{Z-R} = 0.63$	 $c_{Z-R} = 0.60$
Local dominant shapes	 $c_{Z-R} = 0.49$	 $c_{Z-R} = 0.31$
	 $c_{Z-R} = 0.08$	 $c_{Z-R} = 0.07$

Figure 2 Global dominant and local dominant shapes, and their convexity values

After this rough categorization, we propose four detailed categories that are based on specific object attributes and hypotheses we make about the grasping of objects in the categories. These four detailed categories are: 1- *threadlike objects*, 2- *thin objects*, 3- *small objects*, and 4- *large and thick objects*.

When these four detailed categories are applied to *global dominant shapes* (i.e. shape whose convex hull is a good approximation of the object), they give rise to the following four object categories (Figure 1): *rectilinear threadlike objects*, *thin plate-like objects*, *small and thick objects*, and *large, thick and non-segmentable objects*. When they are applied to *local dominant shapes,* they give rise to (Figure 1): *curvilinear threadlike objects*, *thin and curved objects*, *small and thin objects*, and *large, thick and segmentable objects.*

However, global dominant shapes can be considered specific cases of local dominant shapes. The relevance of the distinction lies in the fact that OBB are more likely to adequately represent *global dominant shapes* than *local dominant shapes* for grasping purposes.

Detailed categorization

5.1.1 *Threadlike objects*

A threadlike object is characterized as a set of swept volumes whose trajectories take the form of 3D curves swept by sections having smaller dimensions than the maximum aperture of a human hand so that each section can be enveloped by a wrap. Thus, any part of a threadlike object is a graspable component or plausible grasp location (Figure 3). Some segments of the object offer hand translation and rotation possibilities, while others essentially offer only rotation possibilities.

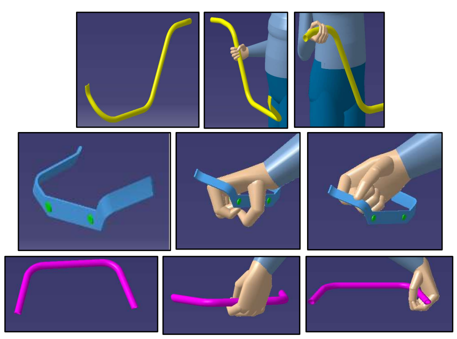


Figure 3 Examples of threadlike objects with grasps manually generated in Catia V5

When the 3D sweep trajectories are rectilinear, the shape is global dominant and categorized as a *rectilinear threadlike object*. Otherwise, the shape is local dominant and categorized as a *curvilinear threadlike object.* Furthermore, at a topological level, certain 3D sweep trajectories are characterized as a single segment between a starting sweeping point and an end point—these are *single-branch threadlike objects*. Others present ramifications in the form of several segments between the starting point, junction points and ending points of the sweep—they are *multi-branch threadlike objects*.

5.1.2 *Thin objects*

Thin objects are surface-like structures whose thickness is much smaller compared to their lateral dimensions. Thin objects seem to offer a variety of grasping possibilities, including using a lateral grasp, along antipodal contact points on its contour, or by positioning two virtual fingers opposing each other on either side of the thickness of the object (Figure 4).

When the surface-like structure supporting the object is a primitive such as a plane, the shape is global dominant and categorized as a *thin plate-like object*. Otherwise, the shape is local dominant and categorized as a *thin and curved object.* In either case (whether global dominant or local dominant), the object can also have holes whose dimensions allow fingers or the whole hand to pass through to grasp the object. Therefore, we distinguish between *thin plate-like objects with useful holes* and *thin plate-like objects without useful holes* and between *thin and curved objects with useful holes* and *thin and curved objects without useful holes* according to the functional relevance of the holes for grasping. The external contours and internal loops of thin objects can then be plausible grasp locations.

Figure 4 Examples of thin objects with grasps manually generated in Catia V5

5.1.3 *Small objects*

Feix *et al.* (2021) studied small cylindrical objects having a diameter of up to 5 cm that can be associated with various translation and rotation possibilities [9]. In-hand manipulation capability, which makes it possible to rotate small objects, is dependent on the objects' overall dimensions. Moreover, according to Xinyu *et al.* (2021), small objects can be fully enclosed by a human hand [46]. Thus, we define small objects as items whose largest diagonal of their OBB is less than *5* cm (Figure 5). This choice of threshold value of 5 cm is based on the conclusion of studies like the one of Feix *et al. (2014)* that 83% of the objects handled in their experiments were held at a location where the *grasp aperture was less than* 5 cm. Small objects can be either *small and thick objects* when they are global dominant shapes or *small and thin objects* when they are local dominant shapes. *Small and thin objects* can also have holes that are useful for grasping (in this case, the functional relevance of a hole for grasping is determined by whether it is possible to introduce a finger in the hole to grasp the object).

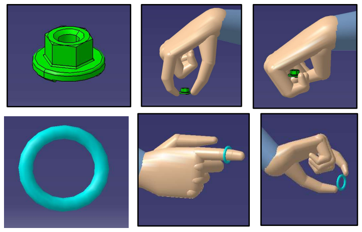


Figure 5 Examples of small objects with grasps manually generated in Catia V5

5.1.4 *Large and thick objects*

Large and thick objects can be categorized as either large, thick and segmentable objects or the large, thick and non-segmentable objects depending on whether they are local dominant shapes or global dominant shapes.

Large, thick and segmentable objects are *local dominant shapes* that are not well approximated overall by their OBB and convex hull. They are characterized as an assembly of thick components with thin components, threadlike components or even convex regions that can be used to grasp the object (Figure 6). Visually, these objects have local surface variations that can be used for grasping. Thus, the overall dimensions of the OBB are such that it is not possible to grasp the object along any of its dimensions but it is possible to use local convex regions or local graspable components to grasp the object.

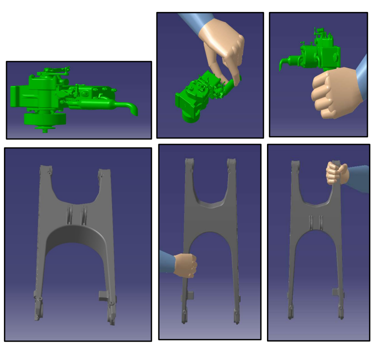


Figure 6 Examples of large, thick and segmentable objects with grasps manually generated in Catia V5

This category can also be further broken down depending on the utility of holes and protrusions for grasping. The resulting categories are: *objects with useful holes* and *objects with useful protrusions*—such as stiffeners affixed internally or externally to one side of the object. In this case, the functional relevance of a hole for grasping is characterized by the possibility of introducing a thumb into the hole and placing the other fingers as another virtual finger on a parallel external face of the object. Therefore, the distance between the hole and the external face should be less than the maximum aperture of a human hand. The functional relevance of a hole for grasping can also be determined by the possibility of passing the whole hand through it in order to grasp the object. The utility of a protrusion is determined by the possibility of placing virtual fingers on two opposable faces of the protrusion to grasp the object.

Large, thick and non-segmentable objects are *global dominant shapes* whose dimensions are too big for a finger-centered type of grasp. Geometrically speaking, the dimensions of the object are such that it would be very difficult to place two virtual fingers on two opposing faces and ensure grasp stability. Thus, visually, the object does not have any prominence that could be grasped with one hand. Consequently, such an object needs to be grasped with both hands and with the palms of the hands placed on two opposing faces located a greater distance apart than the maximum aperture of a human hand. Figure 7 shows an example of such a part.

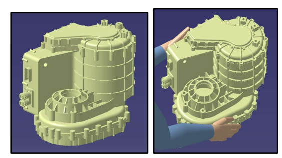


Figure 7 Example of a large, thick and non-segmentable object with a manually generated grasp in Catia V5

6. DISCUSSION

Our grasping-oriented approach to categorizing objects includes a first high-level categorization step and a second more detailed one. Our four proposed detailed object categories are: 1- *threadlike objects*, 2- *thin objects*, 3- *small objects*, and 4- *large and thick objects*. When applied to *global dominant shapes,* they give rise to: *rectilinear threadlike objects*, *thin plate-like objects*, *small and thick objects*, and *large, thick and non-segmentable objects*. When applied to *local dominant shapes,* they give rise to: *curvilinear threadlike objects*, *thin and curved objects*, *small and thin objects*, and *large, thick and segmentable objects*. This grasping-oriented categorization approach was used to manually categorize a subset of 242 real rigid industrial objects. The categorization task resulted in 27.3% *threadlike objects*, 43.8% *thin objects*, 2% *small objects*, 24.3% *large and thick objects*, and 2.6% uncategorized objects. The detailed categorization results by type of dominant shape (global or local) are presented in Table 2.

We then put forwards some grasping hypotheses for each of the object categories proposed to guide the automatic identification of a variety of plausible grasp locations for unknown objects in virtual ergonomics. We do not, however, aim to identify all possible plausible grasp locations for each unknown object. These grasping hypotheses are related to real industrial parts. Realistic objects from GrabCAD are used here for illustration purposes due to confidentiality constraints.

Rectilinear threadlike objects	*05.0%*
Thin plate-like objects	*04.1%*
Small and thick objects	*01.2%*
Large, thick and non-segmentable objects	*01.6%*
Curvilinear threadlike objects	*22.3%*
Thin and curved objects	*39.7%*
Small and thin objects	*00.8%*
Large, thick and segmentable objects	*22.7%*
Uncategorized objects	*02.6%*

Table 2 Detailed categorization results for 242 real industrial objects

Threadlike objects are characterized as a generalization of *rectilinear objects* for *multi-sweep sections* having a 3D curve *sweep path*. They can be grasped by placing two virtual fingers opposite each other on two opposable faces of the object with the maximum aperture of the hand remaining approximately the same regardless of the position of the contact points on the surface of the object. These objects' cross-section dimensions also make it possible to use a wrap-around type grasp to wrap the hand over a section of the object. The grasping hypothesis that we put forward for *threadlike objects* is that the identification of plausible grasp locations can be guided by the objects' 3D skeleton (Figure 8). Then, we can automatically identify plausible grasp locations on *threadlike objects* by applying a cross-section properties analysis to the 3D skeleton as Macloud *et al.* (2019) did [27]. In robotics grasping approaches, Vahrenkamp et al. (2018) for example exploited the mean curvature flow skeleton extraction algorithm of Tagliasacchi *et al.* (2012) [40, 42]. In CAD, other approaches to automatic skeleton extraction exist such as those of Li *et al.* (2015), Huang *et al.* (2013), etc. [14, 22].

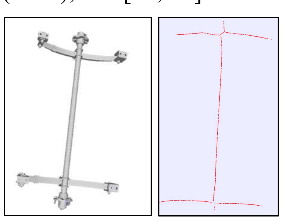


Figure 8 ***Example of a threadlike object and its 3D skeleton***

Thin objects can be either *thin plate-like objects* if they are *global dominant shapes* or *thin and curved objects* if they are *local dominant shapes*. To stabilize a grasp on either type of object, most humans will tend to look for pairs of points on opposed surfaces along the contours in order to apply opposing forces with two virtual opposite fingers. In terms of invariance, translating a grasp along the contour can leave the grasp substantially invariant. However, rotating a grasp perpendicularly to the contour requires changing the hand configuration. The hand palm would need to be opened to place a virtual finger on a face while respecting the local curvatures. Grasping thin parts using local curvatures would not, however, enable opposing forces to be exerted to stabilize the object. Thus, the grasping hypothesis that we propose for *thin objects* is that the contour of *thin objects* as well as their internal loops can offer a variety of plausible grasp locations that support the generation of human-like grasps (See figure 9 - *Color printing is recommended for optimal contour visibility*).

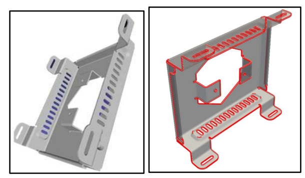


Figure 9 ***Example of a thin object with highlighted contours and loops***

For these *thin objects*, we started experiments with human participants to validate this hypothesis that grasping could be guided by the contours of real thin objects (Figure 10).

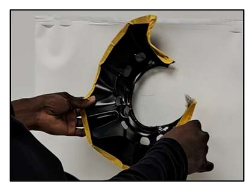


Figure 10 Example of a human grasping a thin object

Small objects are characterized by the fact that the largest diagonal of the OBB is less than 5cm. They can be *small and thick objects* if they are global dominant shapes, or *small and thin objects* if they are local dominant shapes. The area of their envelope is small compared to the area of a human hand. As a result, the grasping options for small objects are almost infinite because a number of within-hand object manipulations are possible. A *small object* can be picked up with two or more fingers, completely wrapped, burped inside the hand, etc. Therefore, the grasping hypothesis we propose for *small objects* is that the entire envelope of the object can serve as plausible grasp locations once opposite faces or a useful hole have been identified. Those grasp location options can serve to generate finger-centered or wrap-around type grasps to enclose the object in one hand (Figure 5).

Lastly, *large and thick objects* are characterized by the dimensions of their OBB and the dimensions of sections that are too large to be grasped by a fully opened hand. For large, thick and non-segmentable objects, this implies that the thumb and a virtual finger are not opposing each other, and the hand palm is placed on a surface of the object. These types of objects are generally grasped with two hands (Figure 7). *Large, thick and segmentable objects*, for their part, have convex and local regions whose dimensions allow the object to be grasped (Figure 11).

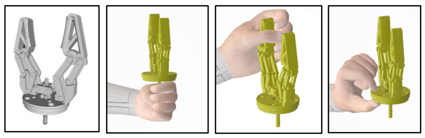


Figure 11 Example of using local regions to grasp a large, thick and segmentable object

Lastly, we recorded 2.6% ambiguous objects that were uncategorized. The ambiguity of these objects stemmed from the possibility of associating them with more than one category, such as *threadlike objects* and *thin objects* simultaneously (Figure 12).

Figure 12 Example of uncategorized object

Having established the grasping-oriented categories of objects, our future works will focus on evaluating the relevance of 3D geometric metrics and 3D CAD shape descriptors for the automatic recognition of unknown objects categories. In the context of category-level grasp planning in robotics for example, Liu *et al.* (2016) used a modify Signature of Histograms of OrienTations (modified SHOT) to automatically recognize the category of a given object [25]. Our future works will also focus on automating approaches to identifying a variety of plausible grasp locations for categories of objects that are priorities for manufacturers. These sets of plausible grasps locations will be determined in accordance with the grasping hypotheses we have put forward and validated by an experiment with human participants.

7. CONCLUSION

Our objective was to propose a grasping-oriented categorization of industrial objects to automatically identify a variety of plausible grasp locations on CAD models of unknown objects in virtual ergonomics. This study is part of a project to improve our industrial partner's Smart Posturing Engine (SPE™) that automatically positions virtual mannequins in a virtual scene. Our grasping-oriented approach to object categorization includes an initial high-level categorization step to distinguish global and local dominant shapes followed by a detailed categorization step. In the latter step, we propose to sort objects into four detailed categories: 1- *threadlike objects*, 2- *thin objects*, 3- *small objects*, and 4- *large and thick objects*. We hypothesize that for *threadlike objects*, the identification of plausible grasp locations can be guided by the 3D skeleton of the objects and an analysis of cross-sections of the 3D skeleton. For *thin objects*, we hypothesize that the contour and internal loops of these objects can offer a variety of plausible grasp locations to support the generation of human-like grasps. As for *small objects*, the entire envelope can serve as plausible grasp locations once opposite faces or a useful hole have been identified. For *large, thick and segmentable objects*, local features can serve as grasp locations depending on the dimensions of the objects' convex and local regions. For *large, thick and non-segmentable objects*, opposable faces on which the palms of the hands can be placed to grasp the object with two hands can serve as grasp locations. Our future work will pertain to develop approaches for automatically categorize unknown objects and approaches for automatically identifying variety of plausible grasp locations on objects of given categories in virtual ergonomics.

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