CAD-driven pattern recognition in reverse engineered models

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CAD-driven Pattern Recognition in Reverse Engineered Models

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Abstract: Today, it has become frequent and relatively easy to digitize the surface of 3D objects and then to reconstruct a combination of geometric primitives such as planes, cylinders, spheres or cones. However, the given reconstruction contains only geometry, no information of a semantic nature used during the design process is included. In this paper, we present a robust method to recognize specific geometric structures which are not explicitly present in an object, such as features and repetitions. These are known as patterns, which are used in the CAD modeling process. Moreover, the digitization of an object often leads to various inaccuracies, and therefore inaccurate extracted primitives. We also demonstrate how recognized patterns can be useful as an application in beautification, which consists of the adjustment of primitive parameters to satisfy geometrical relations such as parallelism and concentricity. Our objective is to design a fast and automatic method, which is seldom seen in reverse engineering. We show the efficiency and robustness of our method through experimental results applied on reverse engineered 3D meshes.

1 INTRODUCTION

An industrial reverse engineering application aims to reconstruct an object as a combination of geometric primitives, from a digitized 3D mesh or a 3D point cloud (Bénière et al., 2013). For example, on manufactured objects, we search for planes, spheres, cylinders, cones and tori. A more advanced objective of the reverse engineering process may also be to retrieve the design intent of an object. To do this, we must take into account CAD modeling rules, which produce semantics in constructed objects.

In this paper, we propose a method to recognize specific patterns from a set of primitives. This allows us to deduce, even for an inaccurate digitized object, geometrical relations given by the original modeling process. Then, we show that these patterns can be used to improve the reconstructed model, for example. This is known as a beautification step (Langbein, 2003), which aims to satisfy the geometric relations between the primitives (*e.g.* parallelism, orthogonality) by regularizing the primitive parameters.

We present previous work on this topic in Section 2. Then, we detail our proposed method in Section 3. Finally, we present experimental results on several 3D meshes in Section 4 and conclude in Section 5.

2 PREVIOUS WORK

During the design process of manufactured parts, particular geometric structures are often constructed according to specific mechanical functions or machining processes. These structures are commonly called *patterns*, and correspond to combinations of primitives which respect some geometrical relations. In reverse engineering, recognizing these patterns allows us to understand relations between the primitives and to retrieve information about the design or the machining process of the part. In this section, we focus on two types of patterns which are features and repetitions.

2.1 Feature Recognition

The first type of patterns contains neighboring primitive subsets which define geometrical structures related to a machining process or a specific tool (Sanfilippo and Borgo, 2016). These structures correspond to *features* (Harik, 2007), which can be specific holes for example. To recognize features, three approaches seem to be favored (Babic et al., 2008). The first one consists of the construction and an analysis of a graph containing relations between the primitives, which can be neighborhood (Lupinetti et al., 2017)

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or geometric relations such as parallelism or concentricity (Wu et al., 2003). Then, the pattern recognition corresponds to a sub-graph detection according to each feature type. The second approach first decomposes the part into small convex volumes, then tries to detect specific volume combinations corresponding to features (Geng et al., 2016). The third approach groups other methods, which can be based on *hints* such as 2D sections of the part for example (Muraleedharan et al., 2018). Other methods have been proposed to recognize patterns, based on neural networks (Jun et al., 2001) or genetic algorithms (Pal et al., 2005). However, these approaches require a large and annotated database, which is out of our scope. Finally, we highlight methods which use systems of rules based on three previously described approaches (Wang and Yu, 2014; Vilmart et al., 2018). These rule systems can be used to infer new information or construct a hierarchical system of features, for example.

However, existing methods seem to have difficulties correctly separating intersecting features. Moreover, some information used to recognize features are specific to a feature type, which can be a problem to extend the method to other features. On the other hand, rule-based methods have been proposed to improve obtained results, by taking the best of the three approaches. In current literature, it seems that a few methods propose to recognize features from primitives extracted from a digitized 3D mesh, which are often inaccurate. It would be interesting to adapt a rule-based system and take into account all the information deduced from both the 3D mesh and the extracted primitives.

2.2 Repetition Recognition

The second class of patterns contains repetitions from a reference geometrical structure, such as a feature, which can be composed of one or many primitives (Urbanic and Elmaraghy, 2008). This *repetition* can then be constructed from a predefined scheme, for example a line or a circle. The main particularity of these patterns is that their components are regularly spaced. For example, a circular repetition places the reference feature duplicated regularly over 360°. To recognize repetitions, a first approach consists in the detection of transformation combinations of a subset of primitives, such as translation, rotation or scaling (Pauly et al., 2008). A second approach is based on a symmetry detection, which allows us to characterize a pattern by a combination of symmetry planes (Vilmart et al., 2018). Other approaches propose to use additional informations such as 2D sections of the object for example (Urbanic and Elmaraghy, 2008). We note that most of the existing methods only propose to recognize repetitions from similar primitive subsets and define the extracted patterns in a reference plane, as in standard CAD modeling processes.

However, most of these approaches are designed for models without inaccuracies. In fact, similarity and placement of inaccurate primitives are more complex and can generate construction ambiguities, particularly when the complexity of the parts increases. Therefore, it seems difficult to use existing methods on reverse engineered models from inaccurate data in a generic manner, without taking particular cases into account.

3 PROPOSED PATTERN RECOGNITION

In CAD modeling, we often construct some patterns of primitives according to standard rules. In our context, we need to recognize them from a combination of geometric primitives. Firstly, we focus on neighbor primitive sets, which can define features. Secondly, we propose to recognize repetitions. In the context of reverse engineering, we also propose an application to model *beautification* (Langbein, 2003), which regularizes primitive parameters with respect to geometric constraints.

3.1 Feature Recognition

In mechanics, each part can correspond to a specific function. When we focus on them more locally, we can also find sub-parts which have their own functions. We call these sub-parts *features*. These features correspond to specific mechanical functions or machining processes, and give some information concerning geometrical relations between primitives. In this work, we focus on two features, counterbored and countersunk holes (see Fig. 1), which essentially imply parallelism and concentricity relations. Since we do not have any *a priori* information on the part, we only analyze the geometry of these structures without infering associated mechanical functions or machining processes. To recognize these features, we propose a rule-based method where the rules are defined by geometrical relations between primitives. First, we construct a graph which contains relations between each pair of primitives: neighborhood, parallelism, orthogonality and concentricity. Then, we define a convexity relation between two primitives by analyzing the convexity of their intersections. Finally, our feature recognition process consists of extracting a sub-graph respecting a set of specific rules for each type of feature.

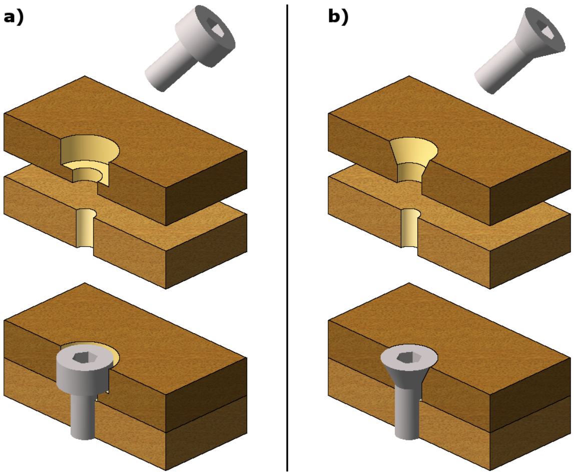


Figure 1: Focus on two features: a) Counterbored hole (or counterbore), b) Countersunk hole (or countersink).

A counterbored hole, or counterbore, is a specific type of drilling (Fig. 1.a). Its principal function is to host and hide a flat head screw, a nut or a ring. A counterbore is composed of: (i) a large cylinder to host the screw head; (ii) a small cylinder to host the screw thread; (iii) a plane to support the screw head. Therefore, we define specific rules allowing us to recognize the geometric structure of a counterbore from a set of primitives and geometrical relations (see Fig. 2.a): (i) the plane is a neighbor of the two cylinders; (ii) the three primitives have parallel orientations; (iii) the two cylinders are concentric; (iv) the two cylinders have different radii; (v) the intersection between the plane and the small cylinder is convex; (vi) the intersection between the plane and the large cylinder is concave. A counterbore is then parameterized by a position, an orientation, two radii, a drilling depth and a counterbore depth. Its position is defined as the intersection point between the plane and the common axis of the two cylinders.

A countersunk hole, or countersink, is another type of drilling (see Fig. 1.b). Its principal function is to host and hide a tapered head screw. A countersink is composed of: (i) a cone to host the screw head; (ii) a cylinder to host the screw thread. Therefore, we define a second set of rules, allowing us to recognize the geometric structure of a countersink from primitives and their relations (see Fig. 2.b): (i) the cone and the cylinder are neighbors; (ii) the cone and the cylinder are concentric; (iii) the intersection between the cone and the cylinder is convex. A countersink is then parameterized by a position, an orientation, a radius, an angle, a drilling depth and a countersinking depth. Its position is defined as the center of the intersection circle between the cone and the cylinder.

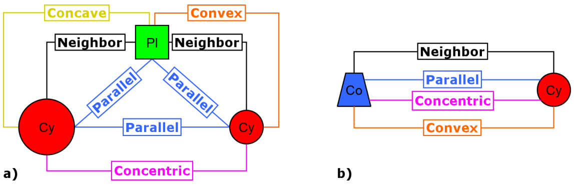


Figure 2: Relation sub-graphs associated to features: a) Counterbore, b) Countersink.

Therefore, each rule set defines a relation sub-graph specific to a feature. The feature recognition is then realized by searching for these specific sub-graphs in a global relation graph between the primitives.

3.2 Repetitions

In mechanical engineering, we often repeat features along specific patterns. For example, aligning regularly spaced fixing holes along a line can improve the global fixation of a large part, increase the production speed or reduce machining costs. Of course, these repetitions can be constructed from varied sub-parts, for economical or esthetic reasons. Consequently, these repetitions contain semantic information, beyond the underlying geometry. In our approach, we propose to recognize repetitions from a feature set. Therefore, a repetition is defined by a set of similar features, regularly spaced along a specific pattern such as a line or a circle. Unlike features, these repetitions are not limited to neighboring components. Then, this recognition allows us to determine relative positions between features.

3.2.1 Feature Similarity

As explained before, a repetition groups similar features. However, in the context of reverse engineering, the corresponding primitives can be inaccurate since they are extracted from inaccurate data. Consequently, we first need to define the similarity between two features. To do that, we propose to compare their parameters, according to predefined tolerances:

- $\Delta_{distance}$: distance tolerance defining two similar positions;
- Δ_{angle}: angle tolerance defining two similar orientations.

Then, we define two types of similarity: partial and integral. The partial similarity consists of the comparison of feature dimensions only. For example, two counterbores are partially similar if their radii and depths are similar according to $\Delta_{distance}$. The integral similarity consists in the comparison of dimensions with $\Delta_{distance}$ and orientations with Δ_{angle}. Hence, integrally similar features are necessarily parallel. We note that partial similarity rules can be adapted by adding or removing conditions, which allows some flexibility in our method. This similarity analysis compares all feature parameters except their positions. Indeed, these can be defined relatively when features are grouped in the same repetition.

3.2.2 Alignment Detection

Linear repetitions, along a line, are most frequently used in CAD modeling. To recognize linear repetitions, we first need to detect aligned features. To do this, we propose to extract a set of axes and points directly from the feature parameters, as illustrated in Fig. 3. In this example, we detect six aligned and parallel features: two countersinks, two counterbores and two simple holes.

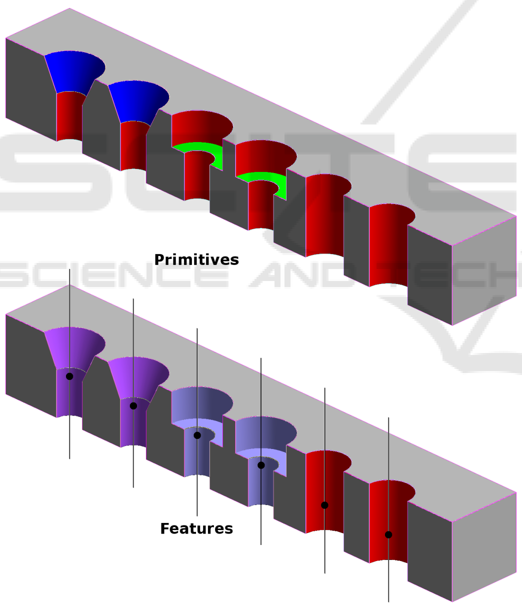


Figure 3: Axis and point extraction from feature parameters. Each axis or point is then common to all the corresponding primitives.

From these axes and points, it is possible to extract alignments in multiple directions. In CAD modeling, repetitions are generally constructed from 2D patterns, designed in a plane. From this observation, we propose to detect repetitions in such planes. In the case of parallel axes, we only use the plane which is orthogonal to these axes, since it allows us to compute orthogonal projection of feature positions. Our feature alignment detection process is illustrated in Fig. 4. We can distinguish two types of alignements: global alignments using partial similarity rules and alignments by type using integral similarity.

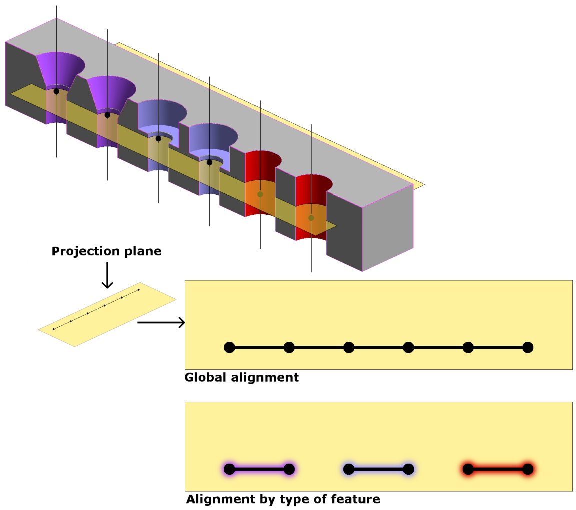


Figure 4: Axis and point alignments as 2D patterns in a reference plane.

The proposed alignment detection consists of seven steps.

1. Construct a plane $\mathcal{P}$ with a reference orientation (according to coordinate system).
2. Project the feature positions $\{p_i\}$ on $\mathcal{P}$, to obtain the positions $\{p'_i\}$.
3. Construct a line $\mathcal{D}$ with a reference orientation which is orthogonal to that of $\mathcal{P}$.
4. Translate $\mathcal{D}$ on a position p'_i. This creates an alignment $\mathcal{A}$.
5. Add to $\mathcal{A}$ the positions $\{p'_j\}$ that are a distance $\delta \leqslant \Delta_{distance}$ from $\mathcal{D}$.
6. Repeat these steps until all the planes, lines and features are treated.
7. Keep only alignments of many features, then compute the final alignment lines by a weighted average. The weights can be given by the area of each feature.

Each alignment is then parameterized by a position, a plane orientation, a line orientation and a feature list. This algorithm retrieves global alignments, but can be extended to alignments by types of features. To do this, we can modify the fifth step to retrieve only positions of the same type or apply integral similarity rules.

3.2.3 Repetition Recognition

As described in Section 3.2.2, a repetition is an alignment of regularly spaced features that are similar.

In CAD modeling, repetitions are commonly constructed from five parameters: (i) a reference plane; (ii) a 2D pattern belonging to the plane, which can be a line or a circle for example; (iii) a reference feature to repeat; (iv) an expected number of feature copies; (v) the distance between two successive features. To generalize the method, we propose to search for combinations of repetitions, allowing us to reconstruct complex feature configurations. For example, a rectangular pattern can be defined as a combination of four repetitions or as a repetition of two sub-repetitions (see Fig. 5).

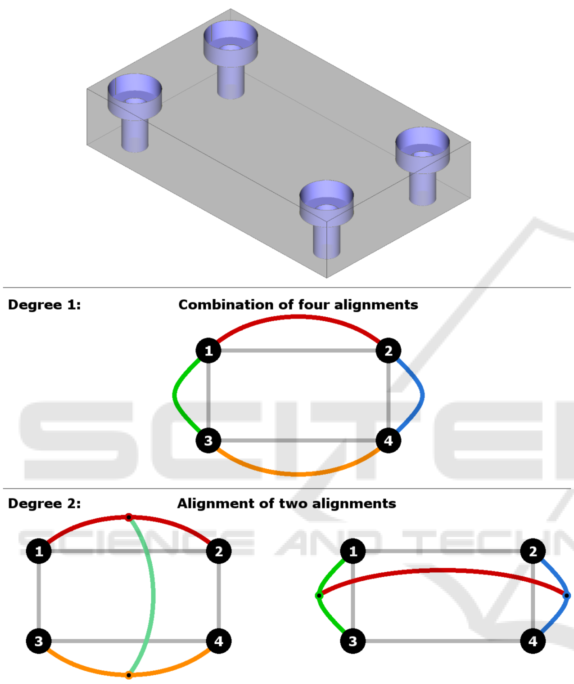


Figure 5: Three interpretations of a rectangular pattern. Black disks correspond to features and colored curves correspond to repetitions.

Therefore, we need to detect repetitions recursively. We then define a new parameter, the *degree*, which corresponds to the recursion depth needed to construct a repetition. We propose to define a repetition p_i^d, where d corresponds to the degree, as a relation R^d between regularly aligned sub-repetitions of lower degree:

$$p_i^d = R^d(p_1^{d-1} ... p_n^{d-1}) \quad \text{with} \quad n \geqslant 2. \tag{1}$$

In our approach, the sub-repetitions $\{p_1^{d-1} ... p_n^{d-1}\}$ must be similar and regularly spaced with a distance δ. The similarity between two repetitions is then defined by comparing their parameters and those of their reference features. According to the pattern type, other parameters need to be compared such as orientations for a line or radii for a circle. Here, a zero-degree repetition corresponds to a feature. In the following, we could also represent a repetition with a tree or a set inclusion (see Fig. 6).

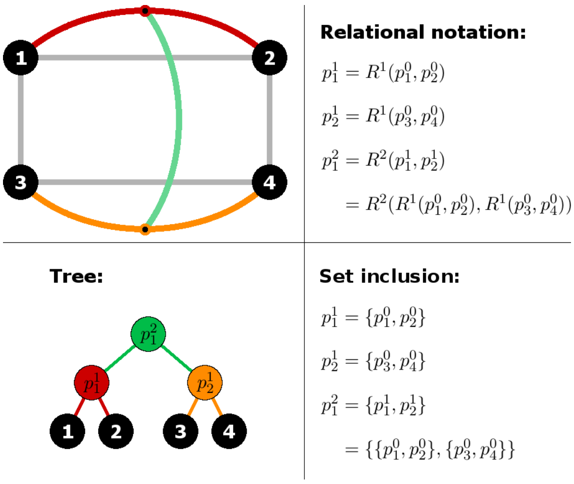


Figure 6: Equivalent notations to represent a repetition.

From the rectangular pattern illustrated in Fig. 5, with a length l and a width w, we can define two equivalent two-degree repetitions: (i) by repeating according to l then w, we obtain the repetition $R^2(R^1(p_1^0, p_2^0), R^1(p_3^0, p_4^0))$; (ii) by repeating according to w then l, we obtain the repetition $R^2(R^1(p_1^0, p_3^0), R^1(p_2^0, p_4^0))$. This equivalence between repetitions can lead to identification problems. Indeed, even if these repetitions result in the same final primitive positions, we do not know which of them was favored during modeling. Therefore, we propose a decision algorithm to keep only the most relevant repetitions. This algorithm is based on a set of predefined rules, which allows for good adaptability. These rules can be designed, for example, to maximize the coverage of the object by repetitions or to reduce the number and degree of repetitions. In our method, four rules are defined to retrieve the most relevant repetitions. These are based on successive minimizations and maximizations of the repetition parameters:

1. maximize the total number of grouped features;
2. minimize the degree;
3. maximize the feature number of sub-repetitions;
4. minimize the distance between sub-repetitions.

The last two points are evaluated from a tree leaf, which corresponds to the reference feature, then by progressively tracing back to the root (see Fig. 7). We note that only a subset of these rules can allow us to decide which repetition to keep. For example, if two repetitions do not contain the same total number of features, the first rule is enough to select the most relevant one. If the selection rules do not allow us to decide which repetition to keep, for example when they have identical parameters as in the case of a squared pattern, then one of the two repetitions is arbitrarily chosen since it does not change the final results.

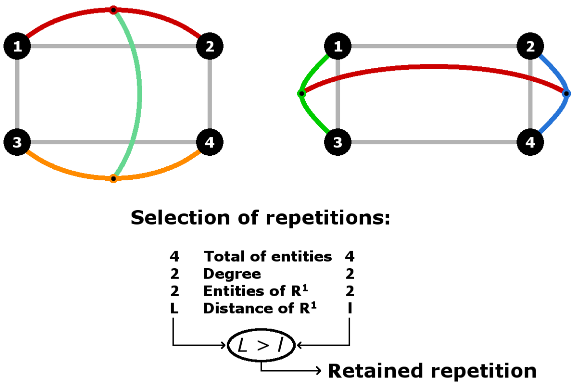


Figure 7: Selection of the most relevant repetition by comparing their parameters, according to predefined rules.

To better correspond to a CAD modeling process, the selected repetitions must not have more than one feature in common. If we take the example in Fig. 8.a, two repetitions have been recognized, which means that the object can be reconstructed in two steps. The first step consists of the construction of the feature p_1^0, then repeating it four times to construct a squared repetition p_1^2. Secondly, the feature p_1^0 is repeated along a line in three times, giving the linear repetition p_3^1. However, both these two repetitions construct the feature p_2^0 whereas we must not construct the same feature many times. Therefore, we need to remove repetitions with more than one common features, and keep at each step the most relevant one according to our rules. This allows us to obtain the configuration shown in Fig. 8.b, for example. This one consists of the repetition of p_1^0 to construct a square, then to repeat p_2^0 to construct p_3^0. In this case, we obtain a unique copy of each feature.

Besides this, some configurations can be ambiguous or composed of many mixed patterns. In this case, many repetition combinations can reconstruct the same object. In Fig. 9, we can see two possible repetition combinations allowing us to reconstruct the same part. The first example is composed of a two-degree and a one-degree repetitions. This combination seems to maximize the total number of grouped features, and therefore seems to be the most relevant one according to our four previously described rules. The second example shows a combination of three one-degree repetitions. This example seems to minimize the repetition degree. To detect the second combination, we only need to use the last three rules. This highlights the adaptability of our algorithm.

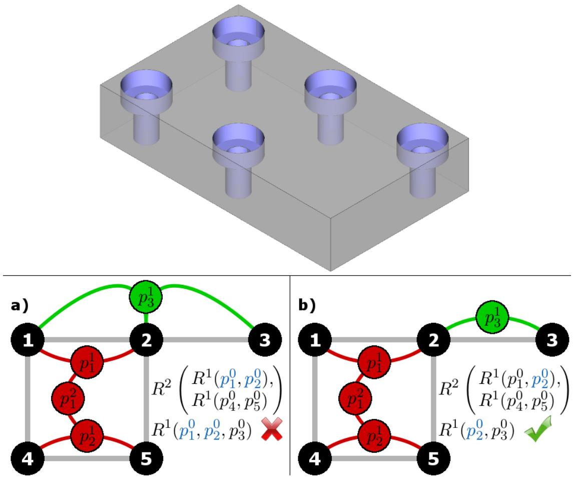


Figure 8: Repetition overlap removal: a) Two common features, b) One common feature.

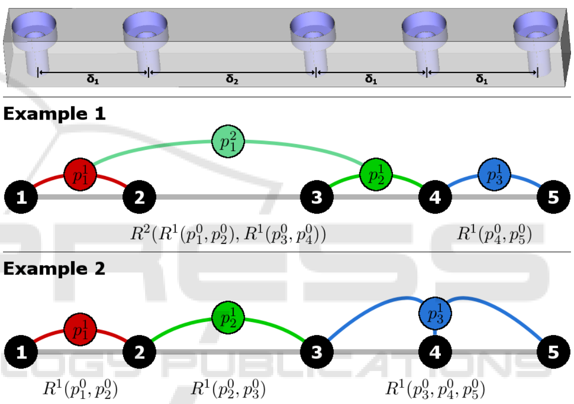


Figure 9: Pattern example which can be described with different repetition combinations.

To correctly recognize repetitions according to predefined rules, we need to take into account all possible combinations of the repetitions which allow us to reconstruct the part. To do this, we propose an iterative algorithm (Algorithm 1). Firstly, we retrieve a set of features $\{p_1^0 ... p_n^0\}$. Then, a feature p_1^0 is defined as the reference feature in repetition recognition. We then search for repetitions of two copies, three copies, up to repetitions of n copies. This recognition is applied iteratively with each feature p_i^0, to obtain all the combinations. These define a set of one-degree repetitions $\{p_1^1 ... p_k^1\}$. The algorithm is iterated on these one-degree repetitions, then on the obtained higher degree repetitions $\{p_1^d ... p_n^d\}$, until no new repetition can be recognized. Finally, a selection step is applied on all recognized repetitions to retain only the most relevant combination. The theoretical complexity of this algorithm can be relatively high, but according to our observations, repetitions generally group small numbers of features.

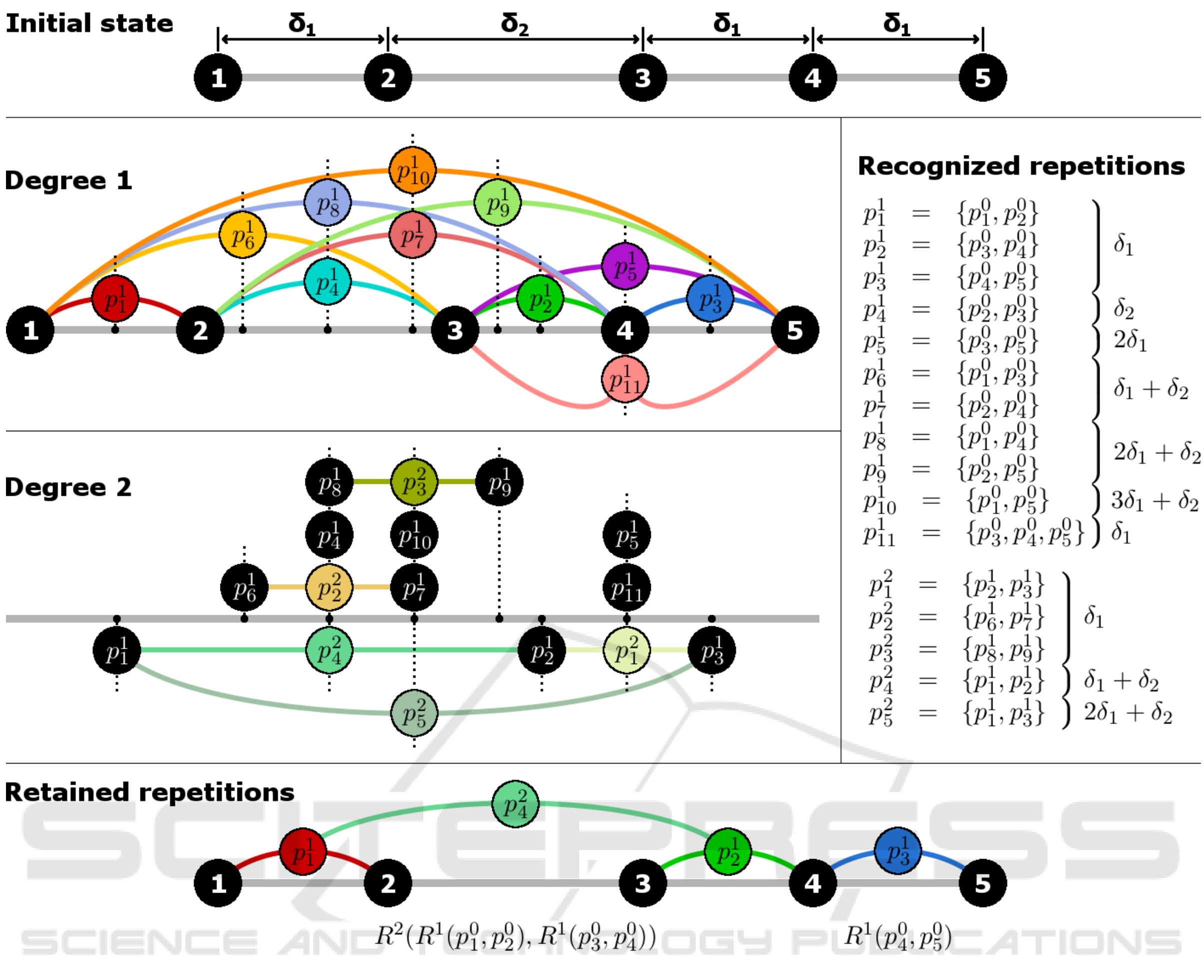


Figure 10: Recognition of all repetition combinations, for each degree, from the object illustrated in Fig. 9.

Algorithm 1: Recognition of repetitions combinations.

Input data: A set of features $\{p_1^0 ... p_n^0\}$
We define a set of repetitions $\mathcal{R} \leftarrow \{p_1^0 ... p_n^0\}$
We define a repetition degree $d \leftarrow 0$
repeat
  for all repetition $p_i^d \in \{p_1^d ... p_n^d\} \subseteq \mathcal{R}$ **do**
    for all number of copies $m \in [2; n]$ **do**
      $\mathcal{R} \leftarrow \mathcal{R} \cup$ Set of repetitions $\{p_1^{d+1} ... p_k^{d+1}\}$ composed of m copies of p_i^d
    end for
  end for
  $d \leftarrow d + 1$
until no new repetition can be recognized
$\mathcal{R} \leftarrow$ Selection of the most relevant repetitions from $\mathcal{R}$
return $\mathcal{R}$

Fig. 10 illustrates the progress of this algorithm on the object from Fig. 9. During the one-degree analysis, eleven repetitions are recognized, with only one which contains three regularly spaced features. During the two-degree analysis, five new repetitions are recognized by grouping similar one-degree repetitions. No three-degree repetition are recognized so the algorithm stops. Indeed, the detected two-degree repetitions are not parameterized by similar distances, and so cannot be grouped.

Finally, the relevant repetition selection analyzes the sixteen obtained repetitions. Our first rule consists of the maximization of the total number of features included in each repetition. So, the algorithm retains the repetitions $\{p_2^2, p_3^2, p_4^2, p_5^2\}$, which group four features each. Our second rule does not allow us to eliminate some of these, since they are all two-degree repetitions. In the same way, our third rule also retains these four repetitions since their sub-repetitions group two features each. Our last rule compares the distances between successive features, for each degree. Firstly, the one-degree repetitions which minimize this distance are p_1^1, p_2^1 and p_3^1. Then, two-degree repetitions are compared if they contain these retained one-degree repetitions, *i.e.*, p_4^2 and p_5^2. Finally, the repetition p_4^2 minimizes the distance and so is retained. During the second iteration, only the repetitions $\{p_3^1, p_5^1, p_9^1, p_{10}^1\}$ do not have more than one feature in common with p_4^2. Again, the last rule, which compares distances, allows us to retain the repetition p_3^1. The selection algorithm finally retains the repetitions p_4^2 and p_3^1, which corresponds to the first combination example in Fig. 9.

In this example, we note that the repetition p_1^2 is equivalent to the repetition p_{11}^1. Indeed, these two repetitions are parameterized by a unique distance δ_1. Moreover, the sub-repetitions of p_1^2 have a common feature. This notion of equivalence could allow us, for example, to reduce the algorithm complexity.

3.3 Application for Beautification

Pattern recognition groups together similar primitives, features and repetitions. However, a reverse engineering process generally approximates primitive parameters from noisy data, such as digitized 3D meshes. In this case, data inaccuracies impact these parameters which are then not exactly identical. Therefore, it seems appropriate to *beautify* the reconstructed model, *i.e.,* to regularize primitive and pattern parameters.

3.3.1 Feature Regularization

As explained in Section 3.1, a feature is defined by some parameters such as orientation, position and dimensions. However, the corresponding primitives can be inaccurate. In this case, they do not exactly respect the geometrical relations induced by the feature design process. We note that in our work, we first regularize orientation parameters to get exactly parallel axes and simplify further analyses (see (Gauthier et al., 2018)). For example, a counterbore can contain two distinct axes, directly extracted from its two cylinders which are approximatively concentric (see Fig. 11). In this case, we need to correctly define the feature parameters, especially when these parameters are common to many primitives. In fact, a counterbore axis can be computed with a weighted mean of two axes with weights corresponding to cylinder areas, for example. We compute a countersink axis in the same way from its cylinder and its cone. The other parameters of these two features are dimensions, which are independant and can be directly extracted from the corresponding primitives. Finally, feature parameters can be regularized according to predefined modeling rules, for example. The corresponding primitives are then regularized according to the regularized feature.

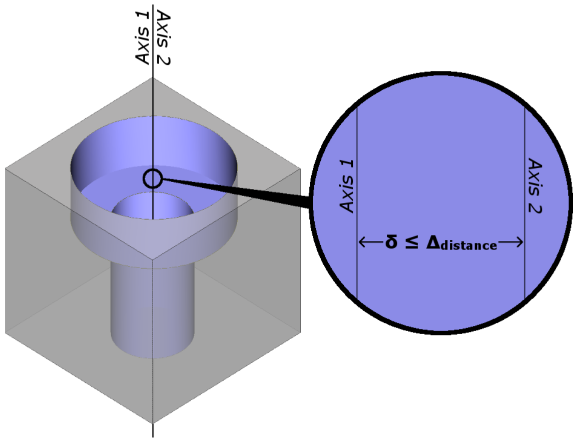


Figure 11: Example of an inaccurate counterbore with two distinct axes from its cylinders.

3.3.2 Repetition Regularization

As described in Section 3.2.3, a repetition is defined by parameters such as a reference feature and the distance between two successive features. However, these parameters can also be impacted by inaccuracies in primitive parameters (see Fig. 12). Indeed, a repetition groups similar features, but not exactly identical ones. Moreover, the distance between successive features can vary when a repetition groups at least three features. In this case, we need to correct the repetition parameters. Therefore, the reference feature parameters can be regularized according to all the grouped features, with a weighted mean, for example. Furthermore, the distance between successive features can be computed from all the different distances contained in the recognized repetition. Finally, repetition parameters can be regularized according to predefined modeling rules, for example. Then, the corresponding features and primitives are made uniform according to the regularized repetition.

4 EXPERIMENTAL RESULTS

In this section, we present experimental results concerning our pattern recognition in reverse engineered models. From complex digitized 3D point clouds or 3D meshes, a reverse engineering process extracts a set of geometric primitives such as planes, cylinders, cones and spheres. We then apply our pattern recognition to this set of primitives.

In Fig. 13.a, we can see the *Moldy* object. From this object, the reverse engineering process extracts 30 primitives (18 planes, 10 cylinders and 2 freeform surfaces). As illustrated in Fig. 13.b, our process extracts four features from these primitives. These

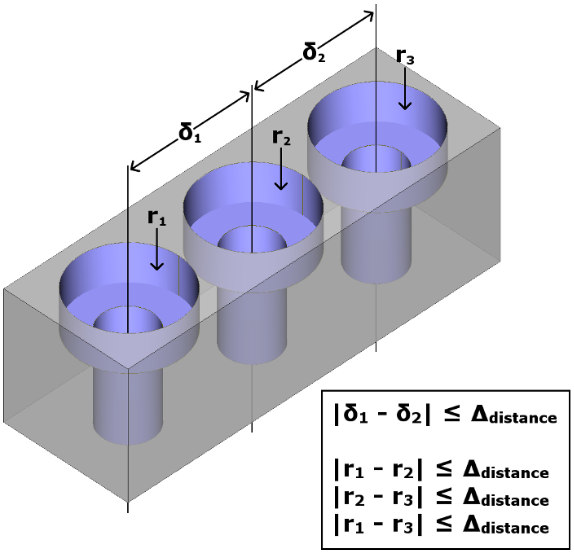


Figure 12: Example of an inaccurate repetition with a variable distance between its features.

four features are parallel counterbores, each defined by two radii and two depths. The four counterbores are parameterized by a drilling radius of $0.187mm$ and a chambering radius of $0.287mm$. The corresponding depths are respectively defined in the ranges of $[0.363; 0.364]$ and $[0.506; 0.508]$. Since the four features are similar, it is then possible to group them into repetitions. The recognition and selection processes give only one relevant repetition, with a degree of two (see Fig. 13.c). This repetition consists in the alignment of two one-degree repetitions, which group two counterbores each (see Fig. 13.d). We also notice that these four counterbores are placed in a square pattern, which certainly corresponds to the original design of the part. Moreover, the center of the obtained repetition is close to the center of the part, which allows us to regularize the repetition position. Finally, all the grouped primitives are regularized at the same time, according to a unique parameter defining the length of the side of the squared pattern. In this result, this length seems to be equal to $5.25mm$.

Fig. 14 shows our results on the *Watertight* object, which is composed of 106 primitives (52 planes, 38 cylinders, 12 cones and 4 torii). This part contains eight parallel counterbores (see Fig. 14.b). The drilling radii are in the range of $[4.95; 4.97]$ and the chambering radii are in the range of $[6.59; 6.96]$. Concerning the depths, we find the ranges of $[10.23; 10.47]$ and $[12.27; 13.05]$. Since the eight counterbores are similar, two two-degree repetitions are recognized. These repetitions group four counterbores each, according to a rectangular pattern (see Fig. 14.c). Fig. 14.d illustrates the obtained repetitions with a schematic representation. The obtained

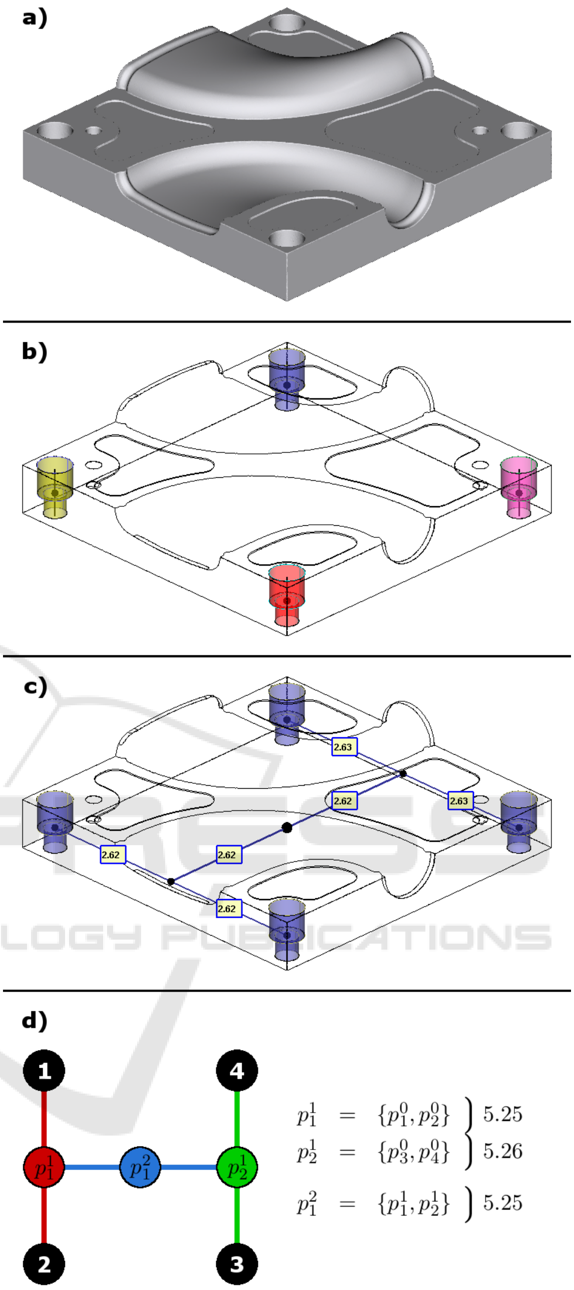


Figure 13: Features and repetitions extracted from *Moldy* object: a) 3D object composed of 30 primitives, b) Features, c) Repetitions, d) Schematic representation.

distance parameters suggest that these repetitions correspond to two rectangles with a length of $82mm$ and a width of $20mm$. The grouped feature positions can then be regularized according to the repetition centers and distances. Moreover, we notice that the two repetition centers are approximatively aligned with the parts center, allowing us to regularize them.

However, these two repetitions are not grouped to-

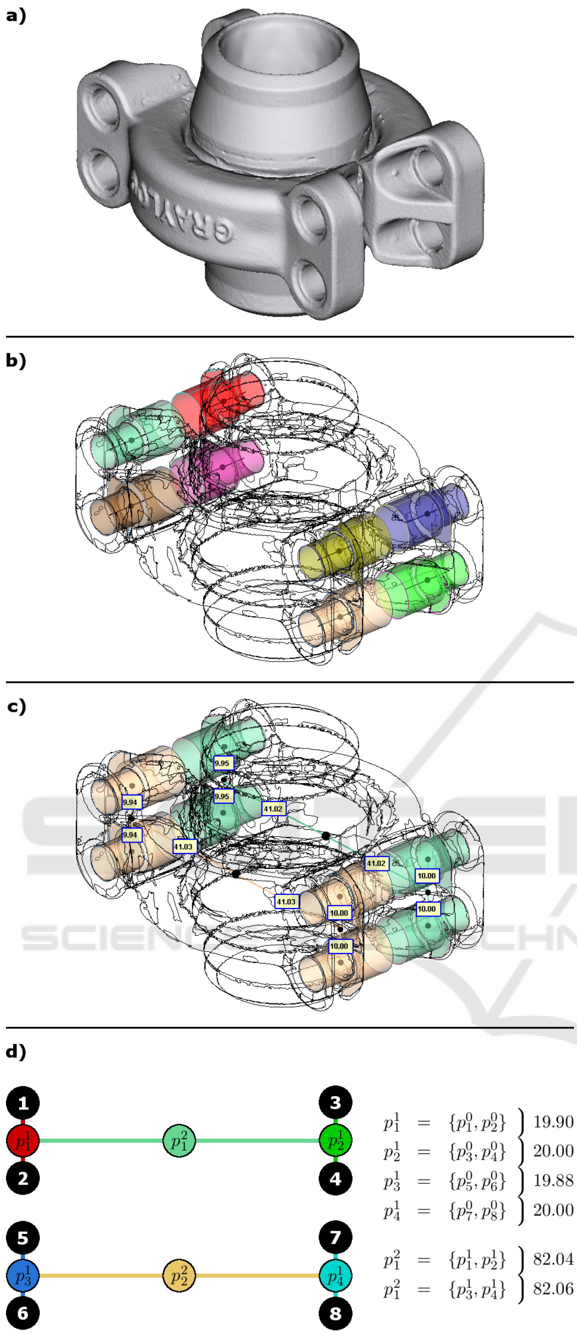
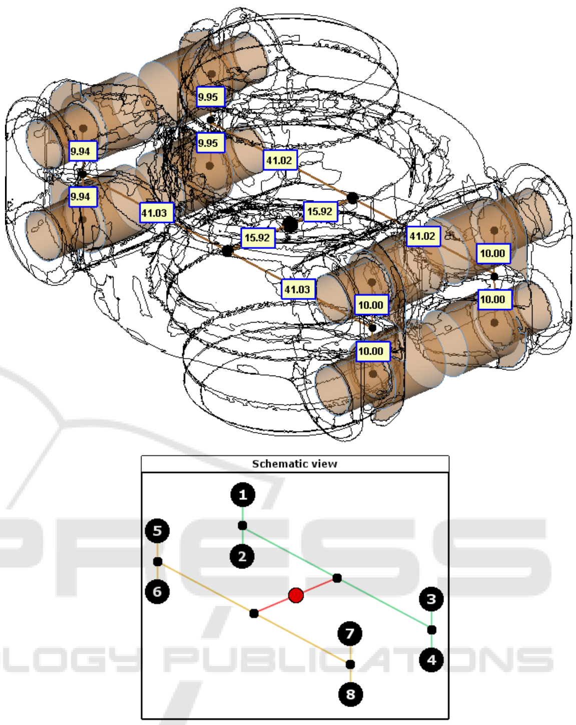


Figure 14: Features and repetitions extracted from *Watertight* object: a) 3D object composed of 106 primitives, b) Features, c) Repetitions, d) Schematic representation.

gether, whereas they seem similar. Indeed, only their orientation are different, and in this case they are anticollinear. In fact, it corresponds to a *mirror*-type design process, which consists in repeating a sub-part of the object with a planar symmetry. We then propose to adapt our repetition recognition rules to detect this configuration. To do this, we just need to define a new partial similarity rule, which allows us to detect an orientation inversion. Finally, we obtain a three-degree repetition, illustrated in Fig. 15. We note that the center of this repetition is close to the center of the part. In this case, we can regularize all the grouped primitives according to the parts center and three distance parameters.



$$R^3(R^2(R^1(p_1^0, p_2^0), R^1(p_3^0, p_4^0)),\\ R^2(R^1(p_5^0, p_6^0), R^1(p_7^0, p_8^0)))$$

Figure 15: *Mirror*-type repetition recognized from repetitions of *Watertight* object, which are illustrated in Fig. 14.

5 CONCLUSION

In this paper, an efficient method has been proposed to analyze a set of geometric primitives and recognize standard CAD patterns. We especially focus on two types of patterns, these are *features* and *repetitions*. We chose to work on primitives extracted from a digitized 3D mesh, using a reverse engineering process. The particularity of these primitives is that their parameters can be inaccurate. Indeed, fabrication and digitization processes are not perfect, and can introduce noisy data.

Our proposed pattern recognition allows us to deduce geometric relations and relative placement between inaccurate primitives. Then, we show that our proposed analysis can be applied to a *beautification* step, which consists of the regularization of primitive parameters to better correspond to the original CAD model. Our experimental results suggest that our approach is robust enough to analyze and correct primitives from a complex digitized part.

Our proposed method is a first step towards a fully automatic reverse engineering process, retrieving the original design intent of a digitized manufactured part. However, it can be difficult to take into account all the primitive placement possibilities in an object, *i.e.,* all distances and proportions possibly used during the modeling process. Therefore, our algorithm is designed to be adaptive and easily extensible, by adding or removing some rules concerning geometrical relations, features and repetitions.

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