



Title:

**Multi-Scale Symmetry Detection of CAD models**

Authors:

Chaoren Li, lichaoren90@outlook.com, State Key Laboratory of CAD&CG, Zhejiang University  
 Ming Li, liming@cad.zju.edu.cn, State Key Laboratory of CAD&CG, Zhejiang University  
 Shuming Gao, smgao@cad.zju.edu.cn, State Key Laboratory of CAD&CG, Zhejiang University

Keywords:

Multi-scale symmetry, symmetry detection, direct modeling, frequent sub-graph mining

DOI: 10.14733/cadconfP.2018.362-366

Introduction:

Symmetries of complex CAD models often overlap and have different forms and scales; see for example Figure 1. Extracting these symmetries can help semantic understanding of the models, and facilitates various industrial applications such as reverse engineering, intelligent direct modeling, model simplification and model retrieval. However, extracting multi-scale symmetries from B-Rep CAD models without any previous feature information remains a challenging problem, and the topic is studied in this paper. Previous methods cannot be adapted to extract meaningful multi-scale symmetries from B-Rep model effectively, as they do not take into consideration the engineering semantics or characteristics of the CAD model.

The paper studies the problem of detecting multi-scale symmetries in a CAD model, and its main contributions are:

1. The multiscale symmetries are detected from a BRep model, which is seldom studied in previous work.
2. The sub-graph mining technique is introduced here to filtering the unwanted symmetries and greatly reduces the efforts of human interaction, and can preserve various symmetries at different scales.
3. Various numerical examples on realistic CAD models are tested to demonstrate the approach's performance.

Main idea:

Our multi-scale symmetry detection algorithm takes a B-Rep CAD model as input and returns multi-scale congruent features and their corresponding symmetry structures or generative model. The main idea is to first extract complete multi-scale congruent features of the model using the method of frequent sub-graph mining, and then to filter meaningless congruent features using heuristic rules, and finally to analyze high-level symmetric structures of every set congruent features.

Four main types of important symmetry relations and symmetry structures are detected for every set of congruent features: reflection symmetry, rotation pattern, linear pattern and rectangular pattern. The algorithmic details are further explained below.

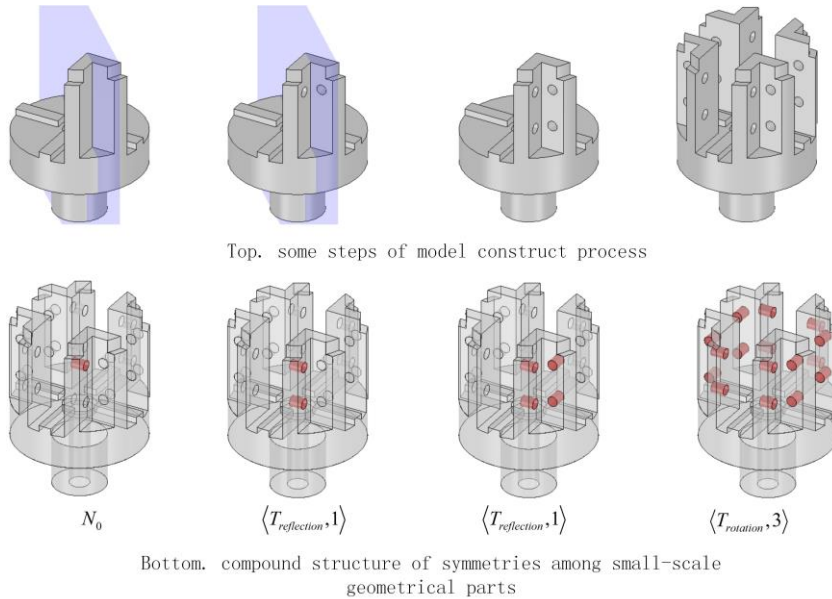


Fig. 1: Different forms of repetition of features and sub-features result in multi-scale symmetries (top) and complex symmetry structures in small scale (bottom), where parts of the same color illustrate congruent feature.

Congruent geometrical parts of a model may be repeating design features. Design features in various domains have different geometrical characteristics, and obtaining them from a B-Rep model, which only contains geometrical and topological information, is difficult. Extracting complete multi-scale congruence features is meaningful as every congruent feature may be what designer needs. The method of frequent sub-graph mining is introduced to mining complete multi-scale congruence features from input model.

There are a large number of congruent features, and redundant congruence relations exists amongst them. A set of heuristic rules are thus used to filter congruent features that are meaningless in most situations so that rich and non-redundant congruence relations can be kept after filtering. Here, the heuristic rules are obtained from the geometric point of view and are domain-independent.

Congruence elements in one congruence feature forms regular structure, understanding the high-level structure helps to capture engineering semantics. Reflection symmetry, rotation pattern, linear pattern and rectangular pattern are four common symmetry types in CAD model, and they are the most important ones among various forms of symmetries, and are detected for every congruence feature.

#### Construction of CLAG:

We transform the problem of extracting congruent features into frequent sub-graph mining from a labelled graph. Thus a Congruence-labelled Adjacency Graph (CLAG) is first used to transform a CAD model into a graph representation. The method of FSM (frequent subgraph mining) is an effective approach to detect frequent pattern in graph dataset [1, 2], and is chosen here to mine congruent features from a CAD model.

The CLAG is constructed as follows. Vertices in CLAG represent faces in model, congruence between faces are used to label vertexes. Arcs in CLAG represent adjacent relations of faces, one arc in CLAG may be related with more than one edges as two faces may have multiple intersection edges. Two arcs are given same label if there exists one-to-one mapping between corresponding edges set and one edge is

not only congruent with the mapped edge but also has the same concavity with it.

The overall steps of our CLAG construction process are described below:

1. Cluster congruent faces of a model, say model A, into the same set, and give each set a different vertex label.
2. Add one new vertex labelled using the result obtained in step 1 to vertex set of CLAG for every face of model.
3. For every two adjacent faces of model A, find a reasonable label. Search consistent arc in the arc set of CLAG whose corresponding two faces have the same adjacency situation. If not being able to find such arcs, generate a new arc label, or use the label of a found arc.
4. Add one new arc labelled using result obtained in step 3 to the arc set of CLAG for every two adjacent faces.

---

**Algorithm 1:** Congruent Features Extraction Using FSM (FSMOfConFeaExtract)

---

**Input :**

A: input B-Rep CAD model  
 CLAG: Congruence-labelled adjacency graph of A

**Output :**

```

{Ci} ← Complete Multi-Scale congruent features Set
1: PatSet ← empty sub-graph pattern set of CLAG
2: EmbeddingsSet ← empty set of Embeddings Set
3: Pi = FFSM-Generate(PatSet, CLAG), generate new sub-graph pattern
4: while Pi is not empty pattern do
5:   {Ei} ← FindEmbeddings(Pi, CLAG), find all embeddings of Pi in CLAG
6:   if cardinality of {Ei} is greater than 1 then
7:     add Pi to PatSet, add {Ei} to EmbeddingsSet
8:   end if
9:   Pi = FFSM-Generate(PatSet)
10: end while
11: {Ci} ← empty set of congruence feature
12: for each embedding set {Ei} in EmbeddingsSet do
13:   {Cj} ← Congruence-Cluster({Ei}, A)
14:   for each congruence feature Cj in {Cj} do
15:     if congruence number is greater than 1 then
16:       add Cj to {Ci}
17:     end if
18:   end for
19: end for
20: return {Ci}

```

---

Extract complete multi-scale congruent features:

The challenge of extracting complete multi-scale congruent features from model is to avoid duplicate computation as abundant overlap exists in different congruent features. How to avoid duplicate computation and extract frequent graph pattern effectively have been well-studied in the field of frequent sub-graph

mining (FSM), which is thus chosen here to mining frequent pattern form CLAG and extract multi-scale congruent features from model.

The overall algorithmic steps are described in Algorithm 1.

#### Congruent feature filter:

The complete multi-scale congruent features extracted above may still be redundant, and are here further reduced using the following three heuristics:

1. Congruence feature whose congruence elements overlap in some areas should be filtered;
2. Maximal congruence feature should be kept;
3. Congruence feature whose congruent elements are consistent with local feature should be kept.

#### Symmetry structure detection of congruence feature:

Symmetry structure detection of a congruence feature  $N$  can be formalized as finding a compact generative model that covers as much congruence elements of  $N$  as possible. A multi-scale congruence feature based symmetry structure detection algorithm is proposed for this. The algorithm is based on the observation that a CAD model is formed from repeated features and sub-features recursively. For example, a feature contains four repeated sub-features  $G_i (i = 0, 1, 2, 3)$  that form a rotation pattern. The symmetries are detected within the congruent set based their recitation.

#### Experimental results:

Various complex CAD models are used to test performance of the proposed approach, and the result on one example is shown in Figure 2. For each model, borders of the source models are marked red, figures sharing same boarder colors denotes that they share the same scale of symmetries. As congruent elements of congruent feature are adjacent, we use one extra figure of border in dashed line to represent congruence elements.

#### Acknowledgement:

The work described in this paper is partially supported by the NSF of China (Nos. 61472356, 61210007).

#### References:

- [1] Huan, J.; Wang, W.; Prins, J.; Yang, J.: Spin: mining maximal frequent subgraphs from graph databases. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pages 581-586. ACM, 2004.
- [2] Jiang, C.; Coenen, F.; Zito, M.: A survey of frequent subgraph mining algorithms, Knowledge Engineering Review, 28(1), 2013, 75-105. <https://doi.org/10.1017/s0269888912000331>

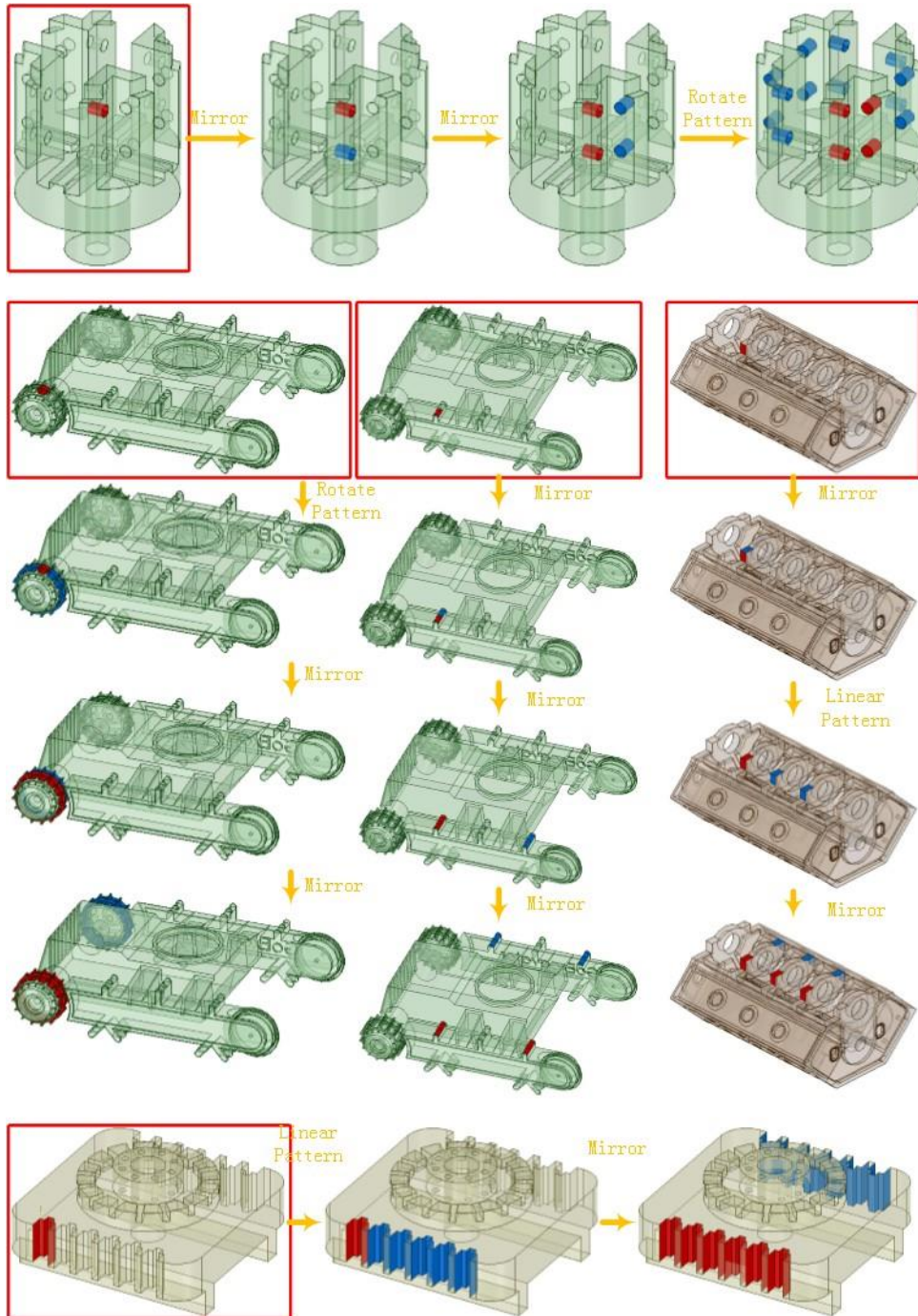


Fig. 2: Results of multi-scale symmetry detection on various CAD models.