2D CAD Data Mining Based on Spatial Relation

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Abstract

In this research, we propose CAD data mining technique to obtain semantic elements without prior knowledge about plans being designed. Our method consists of two steps. The first step is to extract frequent spatial relations between figure elements in CAD data as clues to the semantic elements. These relations are modeled as topology graph and are analyzed by a graph mining method. In the second step, valid semantic elements are specified by eliminating geometrically unnecessary figure elements through inferring every affine transformation between sets of figure elements having the same frequent spatial structure. In the experiments, the proposed method could extract semantic elements like electrical symbols from floor plan data without prior knowledge about the symbols.

1. Introduction

In recent years, CAD is widely used in designing. Using CAD, designers can save storage space and can design many plans easily by reusing existing data. In that reuse, CAD should be able to retrieve the desired existing plans similar to the one being designed right now from enormous amount of CAD data in the database. At present, however, many users do not master how to exploit CAD functions of structuring the data (for example, giving attributes, grouping, layering, etc.). Only experienced users, who know if the required plans exist and where they are, can retrieve and reuse the similar existing plans from unstructured CAD database. For this reason, the technique of extracting similar structures automatically from CAD data is required.

In this paper, we propose a method for extracting frequent similar patterns in CAD data. This method is expected to make it easy to reuse CAD data because the use of the mining results will enable designers to classify and relate similar substructures latent in unstructured CAD database. This will lead to the automatic structuring of CAD data. We call the frequent structure in CAD data semantic element because the parts appearing many times in many plans would represent some meanings.

Our method extracts candidates of the semantic elements by mining graphs representing spatial relations between figure elements, and sorts out well-taken semantic elements from the candidates by inferring affine transformations among them. Since topology of figure elements in the semantic element is invariant to difference of designers, we use a spatial relation graph of the figure elements called topology graph to reveal their own configuration. However, even if parts of the topology graphs match each other, they do not always represent the same visual structure. Therefore our method determines conclusive results by checking if valid affine transformation can be inferred between candidates of semantic elements based on the assumption that the semantic elements are placed on plans through the affine transformation like displacement, rotation and scaling.

2. Related Works

Many studies on CAD have been accomplished by many researchers. In the field of similarity search, [1] and [2] retrieve similar drawings using graphs which represent spatial relations between figure elements. [3] and [4] retrieve similar forms in the drawings by evaluating their own point clouds or vectors. In the field of mining CAD data, [5] and [6] clusters similar shapes hierarchically using their own point clouds or vectors.

Feature of our method is that spatial relations between figure elements are represented by graph, and

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a mining technique is applied to the graph to obtain semantic elements without prior knowledge. Since this graph represents only the topology of figure elements, tiny difference of their configuration caused by the difference of designers is not reflected. Thus the semantic elements can be extracted by mining regardless of the difference of designers.

3. Topology Graph Mining

Our method represents spatial relations between figure elements in plans with topology graphs. Topology graph is invariant to affine transformation of figure elements (displacement, rotation, scaling) and is not affected by the subtle difference of their configuration caused by the difference of designers. By mining the topology graphs, sets of the figure elements which have frequent configurations can be extracted. They are candidates of the semantic elements having some kind of meanings.

3.1. Topology Graph

In the topology graphs, nodes and edges represent figure elements and relationships between them respectively. Each figure elements in CAD data is represented as f_i. Since each figure element in CAD has its type (line, circle, …etc.) and its control points (start point, end point, center, …etc.), it can be expressed as $f_i=(t^{f_i}, \{\boldsymbol{p}^{f_i}{}_n\})$, where t^{f_i} and $\{\boldsymbol{p}^{f_i}{}_n\}$ shows the type and the set of control points of the figure element f_i. To deal with topological information, the proposed method adds the relationships $\{(f_i, f_j)\}$ between figure elements which touch or intersect with each other. From the above, CAD data is modified to the topology graph $\mathbf{G}=(\{f_i\}, \{(f_i, f_j)\})$. In the graph, a kind of a figure element is represented as a node label. Node label is a digit which a kind of figure elements is assigned to as shown in Figure 1. Its relationships are represented as edge labels. We call the edge labels topology data.

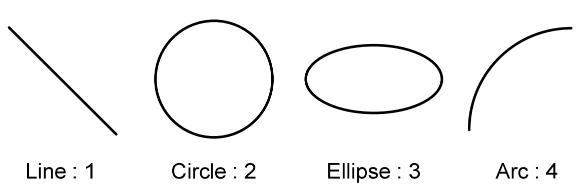

Figure 1. Digits assigned to figure elements

The topology data represent relationships between components of figure elements (area, boundary and set of end points) and consist of five digits. First digit represents spatial relation between figure elements. If the spatial relation between the figure elements is inclusion (or intersection), first digit is 2 (or 1). Second digit represents the relationship between the boundaries of the figure elements and is the number of the intersections of the boundaries. If there are an infinite number of the intersections, let the second digit be 9. Third digit is the number of end points which are included in the area of the other figure element and represents the relationships between the area and the end points. Fourth digit is the number of the end points which are on the boundary of the other figure element and represents the relationships between the boundary and the end points. Fifth digit is the number of the end points which share the ones of the other figure element and represents relationships between the end points. Examples of the topology data are shown in Figure 2. Topology data is invariant to the affine transformation of figure elements because it considers only the spatial relationships between components of figure elements. Topology graphs are built by analyzing the arrangement of the figure elements in CAD data and using the labels described above.

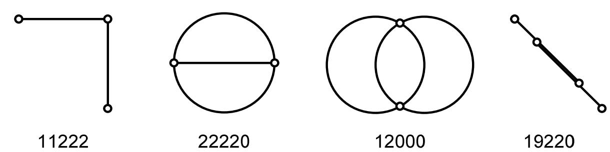

Figure 2. Examples of topology data

3.2. Mining of Topology Graph

By mining the topology graph, our method extracts frequent patterns of the subgraphs as candidates of the semantic elements. Our method uses GASTON graph mining algorithm [7], which works efficiently, especially for sparse graphs. Since the number of the edges in the topology graphs are generally much less than the possible number of edges, this algorithm works very fast.

Candidates of the semantic elements which have the same topology subgraph will have the following undesirable properties. One of the properties is that correspondence between figure elements and the one between their control points cannot be decided by topology subgraphs as shown in Figure 3. The other property is that the same topology subgraphs do not always represent the same configurations in the plans as shown in Figure 4.

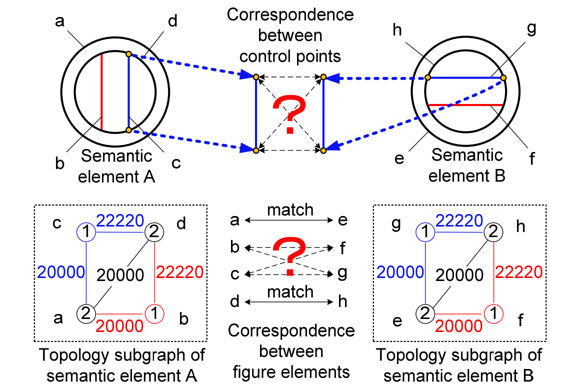

Figure 3. Property on the correspondences

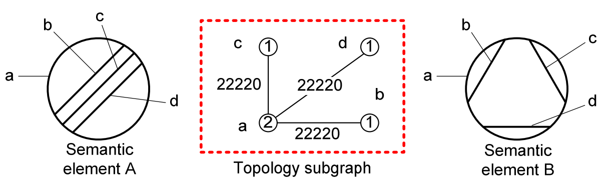

Figure 4. Property on the same topology subgraphs

4. Estimation of Affine Transformation

After mining the topology graphs, our method solves the problems caused by the properties of the semantic element candidates described in the previous section by estimating affine transformation between the candidates having the same topology subgraphs. Our method judges that the candidates are correct by checking if valid affine transformation can be estimated among the candidates under the assumption that the semantic elements are placed in plans through affine transformation.

As shown in Figure 5, we denote by $\mathbf{C}^F$ the sets of all possible combinations of figure elements obtained from the result of the topology graph mining. In addition, in a case of a figure elements combination $c \in \mathbf{C}^F$, the sets of combinations of control points are denoted by $\mathbf{C}^P{}_c$. Our method minimizes the standard deviation of errors between control points corresponding with each other as follows:

$$d = \min_{\mathbf{C}^F} \min_{\mathbf{C}^P_c | c \in \mathbf{C}^F} \min_{\boldsymbol{a}} \left(sd\left(\{ |\boldsymbol{s}(\boldsymbol{p}^f_n, \boldsymbol{a}) - \boldsymbol{p}^{f'}_m | \,|\, (f, f') \in c,\ (n,m) \in \mathbf{C}^P_c \} \right) \right)$$

where $sd(\{v\})$ is the standard deviation of the values $\{v\}$. $\boldsymbol{s}(\boldsymbol{p}, \boldsymbol{a})$ is the point translated from the point $\boldsymbol{p}$ through affine transformation whose parameters are $\boldsymbol{a}$. The affine parameter $\boldsymbol{a}$ minimizing d is calculated using the method of least squares, where Lagrange multiplier method is used to obtain the least square solution [8]. If d is smaller than a threshold, it can be said that the sets of figure elements have the same topology and that one of them can be transformed from the other through affine transformation as shown in Figure 5. This means that they represent the same semantic information.

In this process, thresholding d starts from the pairs of figure element sets having large topology subgraphs. If they are judged to be the same semantic elements, the figure elements in them are excluded from the estimation thereafter to avoid extracting their substructures as other semantic elements.

Our method applies this estimation of affine transformation to all possible combinations of the results of the topology graph mining.

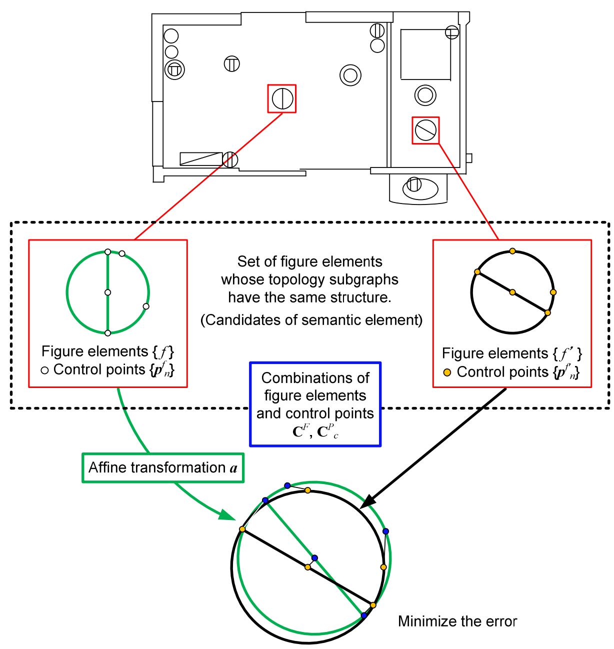

Figure 5. Estimation of affine transformation

5. Experiment

We implemented the proposed method on a PC and applied it to some CAD data to confirm the validity of our method. The CAD data was made with Microsoft Visio and the kernel and GUI of our system were programmed with Visual C++ and Visual Basic under Windows Vista environment.

In this experiment, we used CAD data of 42 floor plans where there exist eight types of electrical symbols, which are illustrated in Figure 6. These floor plans were drawn by 6 persons.

In the experiment, we refer to accuracy rate and extraction rate to evaluate the performance of the proposed method. The accuracy rate is the ratio of semantic elements extracted correctly by our method to all of the extracted semantic elements. Extraction rate is the ratio of semantic elements extracted correctly by our method to all of the electrical symbols placed in the floor plans.

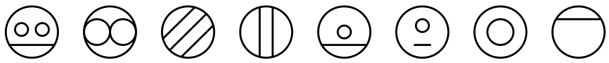

Figure 6. Electrical symbols

First, we built topology graphs of all floor plans and applied the topology graph mining to the graphs with the support 1.0. The support is the ratio of the plans that the frequent subgraph appears to all of those and can adjust the sensitivity of the mining performance. As the result of the topology graph mining, 12 kinds of topology subgraphs were extracted as candidates of the semantic elements as shown in Figure 7. In the extracted topology subgraphs, 5 kinds of electrical symbols existed. The remaining 3 kinds of electrical symbols could not be extracted because of the following two reasons. One of the reasons is that the unextracted electrical symbols were placed in few floor plans. The other reason is that some topology data has changed caused by slight errors of placed positions of figure elements, which, for example, did not reach to another one though they must touch with each other and vice versa as shown in Figure 8. Since 7 erroneous topology subgraphs were extracted, accuracy rate of topology graph mining was 66%.

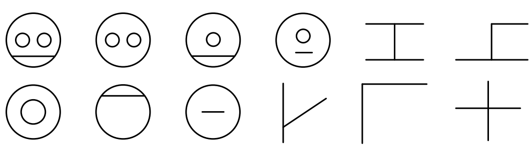

Figure 7. Result of topology graph mining

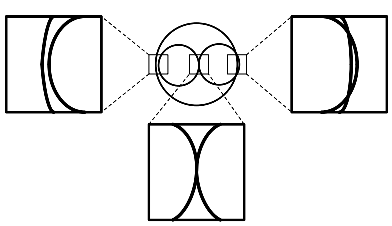

Figure 8. Example of slight errors

Next, we eliminate the wrong candidates of semantic elements by applying the estimation of affine transformation. We applied the estimation of affine transformation among the candidates of semantic elements extracted by topology graph mining. The threshold for d was set to be 1.0. This threshold was determined experimentally. In this step, erroneous candidates would be eliminated and the correspondence between figure elements and that between control points can be derived. In the result, accuracy rate was 72% which became higher than that of topology graph mining. However, this step has two problems. One of the problems is explosion of the combinations of affine transformation caused by considering all possible correspondences between candidates of semantic elements, their figure elements and their control points individually. The other problem is that not all of incorrect candidates were eliminated because similar configurations existed among them. Figure 9 shows an example, where the figure elements are arranged similarly though they do not represent electrical symbols.

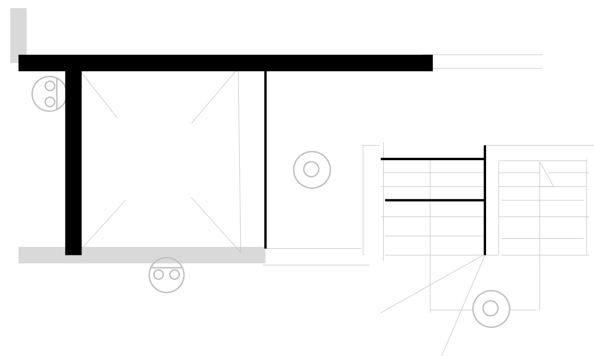

Figure 9. Example of erroneous candidates having similar configuration

At the end, the system showed the user the obtained results judged as semantic elements and requested the user to select correct semantic elements from the results through GUI. In this step, wrong semantic elements were eliminated greatly, and accuracy rate rose to 92%. The work of the users is light because they only select correct semantic elements. Finally, 82% of electrical symbols placed in floor plans could be extracted. Figure 10 represents one of the resultant floor plans. Table 1 is accuracy rate and extraction rate of each step.

6. Conclusion

In this paper, we proposed CAD data mining technique to obtain semantic elements without prior knowledge about plans being designed. Our method extracts candidates of the semantic elements by mining graphs representing spatial relations between figure elements, and sorts out correct semantic elements from the candidates by inferring affine transformations among them. In the experiment, 82% of electrical symbols placed in floor plans could be extracted through the interaction with the user. However, some electrical symbols were not extracted in the case that the electrical symbols were placed in few floor plans and that topology data was changed by the slight error of figure element positions.

We will mention the future plans of this research in conclusion. For improving the extraction rate, it would be efficient to decrease the support value of the graph mining method. But this produces a lot of frequent topology subgraphs, which will lead to the explosion of the combinations of the figure elements and of those of the control points. To avoid this problem, it is desired to develop a new figure-oriented mining method, which can eliminate geometrically inconceivable combinations of the figure elements through the mining procedure and decreases its computation time. In addition, it is also needed to improve the topology data for making it robust to the unexpected displacements in the positions of figure elements.

In improving the accuracy rate, we should not exploit the knowledge about the target data to sort out the results because the use of it is against the objective of this research. We believe that the interaction with the user is the only way to remove the erroneous results. To realize this, more user friendly GUI should be developed.

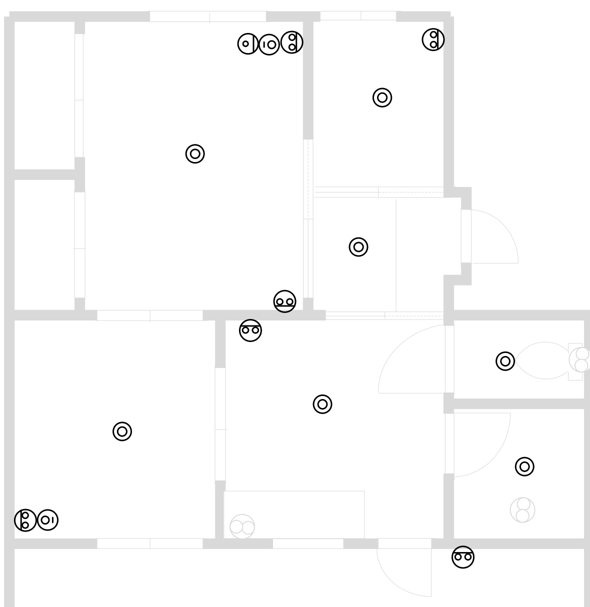

Figure 10. Example of result

Table 1. Accuracy rate and extraction rate

	Accuracy rate	Extraction rate
Topology graph mining	66%	82%
Topology graph mining and affine transformation	72%	82%
Topology graph mining and affine transformation and interaction with user	92%	82%

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