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Clustering of architectural floor plans: A comparison of shape representations

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ABSTRACT

Generative design methods are able to produce a large number of potential solutions of architectural floor plans, which may be overwhelming for the decision-maker to cope with. Therefore, it is important to develop tools which organise the generated data in a meaningful manner. In this study, a comparative analysis of four architectural shape representations for the task of unsupervised clustering is presented. Three of the four shape representations are the Point Distance, Turning Function, and Grid-Based model approaches, which are based on known descriptors. The fourth proposed representation, Tangent Distance, calculates the distances of the contour's tangents to the shape's geometric centre. A hierarchical agglomerative clustering algorithm is used to cluster a synthetic dataset of 72 floor plans. When compared to a reference clustering, despite good perceptual results with the use of the Point Distance and Turning Function representations, the Tangent Distance descriptor (Rand index of 0.873) provides the best results. The Grid-Based descriptor presents the worst results.

1. Introduction

Generative design methods are commonly used in architectural design. These methods have several applications in the design of structural elements, facade layout, space planning, optimisation of building form, replication of architectural styles, and urban design. The main goal is to assist building design practitioners in exploring a larger set of solutions, which a traditional trial-and-error process could never achieve. However, one of the drawbacks is that they may produce an excessive number of solutions for a human to cope with; moreover, it is just not feasible to rate solutions according to a performance criterion and then select the top-ranked ones, especially for unclear and subjective problems. An alternative approach is to organise the generated data into groups determined by common features. This allows the decision-maker to compare group types before analysing specific solutions. Therefore, to facilitate the decision-maker's task of comparison and selection, this paper presents an unsupervised clustering technique using four different shape representations. The method and the performance of these shape descriptors is analysed in a computer generated architectural floor plan showcase.

This is a typical task for machine learning techniques. In the field of machine learning there are two main subfields dealing with organisation of data: classification and clustering. While the former is used to label data according to pre-defined classes, the latter deals with unlabelled data and the task is usually to create partitions in the data while making coherent groups according to some defined metric. This is a process of identifying structures in unlabelled datasets regardless of the data type. Han and Kamber [1] classified clustering techniques into five categories: partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods.

Clustering techniques have been applied in diverse areas. Some of the most relevant applications include the classification of textual documents [2], document navigation for search engine optimisation [3–5], resource project scheduling [6], point cloud simplification [7,8], time series analysis and clustering [9], image clustering [10], face expression [11], database retrieval of mechanical objects [12,13], and sketch recognition [14].

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The clustering of objects, according to their shape, has also been previously applied in diverse fields. The correct representation of the shape has a significant impact on the matching correctness of the algorithms [15]. For instance, Chang et al. [16] proposed a shape recognition scheme where the representation corresponds to the distance of feature points in the shape's boundary to the centroid. This shape representation presents the property of being invariant to translation as the boundary is fixed in relation to the centroid independently of its global position. As the distances of the feature points are ordered and divided by a minimum distance, this also results in invariance to scaling, rotation, and reflection. Instead of only considering the shape feature points, Yankov and Keogh [17] used the entire contour for the shape representation and a nonlinear reduction technique to cluster pathological cells.

Arkin et al. [18] represented a polygonal shape by its turning function. The shape descriptor consists in measuring the angle of the counter-clockwise tangent to the x-axis in each of the feature points in the polygon. Therefore, the values vary between $-\pi$ and π. As the polygon is scaled to have a length of 1, in addition to being translation invariant, the representation is also invariant to scaling. However, results depend on the starting point and the polygon's rotation and reflection.

Sajjanhar and Lu [19] suggested a grid-based representation where a shape is placed, rotated, and scaled to fit a square grid. For each cell in the grid a binary value is determined: 0 for empty and 1 for filled. Although this representation guarantees translation and scale invariance, if the grid is adaptive, the scaling is only invariant to one of the axes—the rotation invariance is dependent on the rotation of the grid to match the same shape orientation. Also, as may be expected, the results vary according to the grid size, as this changes the capability to capture the shape's details.

Siddiqi et al. [20] used a shock graph to capture the effects on the bounding contours of the singularities in the shape structure. The graph is determined according to a set of rules in a shock graph grammar which reduces it to a rooted shock tree. A recursive algorithm is then used to match two shock trees, starting from the root and proceeding through the subtrees in a depth-first approach.

Belongie et al. [21] presented an approach to measure similarity of shapes by considering the distribution of the remaining points in each reference point. As corresponding points in two similar figures have similar contexts, a transformation is used to align two shapes. The dissimilarity between them is calculated by summation over the errors between the corresponding points in the transformation.

Aiming to retrieve shapes from a database, which are similar to a query shape, Tan et al. [22] proposed a new representation based on a centroid-radii approach. According to the authors, this approach allows the modelling of convex, concave, and hollow shapes. The representation consists of a set of vectors, each one measured at regular intervals from the centroid of a concentric ring.

In Klassen et al. [23], the shapes are considered to be planar closed curves represented either as direction functions or as curvature functions. In this manner, shapes may be modelled as stretchable, compressible, and bendable strings along their extensions that are constructed from spaces of parametric curves [24,25]. Geodesics are used to determine the dissimilitude between shapes.

Ling and Jacobs [26] classified shapes by using an inner-distance to build the shape representation of the structure or articulation parts. The inner-distance is the length of the shortest path between two reference points on the shape boundary and allows the creation of articulation invariant representations.

Shen et al. [27] proposed a method to group planar figures by their skeleton graph. The clustering is carried out by determining the common internal shape structure that belongs to the same cluster. The data is grouped by using an agglomerative clustering algorithm.

In architecture, Cha and Gero [28] investigated shape patterns to determine if any similarities, relationships, and physical properties could be recognised. de las Heras et al. [29] used run length histograms as a perceptual representation of floor plans made by architects. This approach allows the retrieval of designs with similar properties from a database. Dutta et al. [30] used a graph-based method to identify symbols in floor plans such as furniture and openings.

However, despite all of the mentioned approaches/methods, the use of clustering techniques has yet to be used to group designs in the case of automatic generation of floor plans. In a previous study, Sousa-Rodrigues et al. [31,32] conducted an online survey directed at design and construction experts—mostly architects, engineers and architecture undergraduates—in which the majority of respondents considered the overall shape of floor plans as the most important similitude feature. This highlights the importance of having perceptually accurate algorithms for the automation of this task.

In this paper, four shape representations are studied as floor plan design descriptors under the same settings. All descriptors are vectors of similar length, and all are used to partition the same dataset with the same clustering algorithm. Three of the four shape representations are known descriptors: these are the distance to centroid [16], the Turning Function [18], and the Grid-Based model [19]. The fourth and last shape descriptor is a novel representation specifically created to capture orthogonal floor plan shapes. It consists in calculating the distance of the tangent lines to the geometric centre of the shape. The clustering procedure is an agglomerative hierarchical algorithm with Ward linkage [33] and Euclidean distance as a dissimilarity measure. The advantages and disadvantages of each shape representation are analysed in a showcase with 72 floor plan designs. These designs were generated using a specific algorithm, named Evolutionary Program for the Space Allocation Problem (EPSAP) [34–36]. The EPSAP algorithm generates alternative floor plans according to the user's specifications.

After this introductory section, Section 2 describes the methods applied to the clustering of the floor plans designs. In Section 3 the results for a showcase of a single-family house are presented and compared to a reference clustering partition. The discussion of the relevant results follows in Section 4, as well as the analysis of the applicability of the descriptors. Finally, conclusions are drawn and future work is outlined in Section 5.

2. Methodology

To determine the most suitable shape representation to be used in the cluster of orthogonal floor plans, three shape descriptors inspired by previous works and one new descriptor were implemented. These descriptors have the same vector length and shape matching algorithm using the Euclidean distance to calculate the dissimilitude between the shapes. Therefore, the computational burden is equal for the four approaches. A specific algorithm generated a dataset of floor plan designs. This synthetic dataset does not require a pre-processing mechanism for denoising the shapes, nor the application of a dimensionality reduction technique. Therefore, the focus is on the perceptual quality of the results of each shape descriptor.

2.1. Shape representation

The representation of continuous features plays an important role in machine learning techniques, either because the machine learning technique itself requires a nominal feature space—nominal features describe qualitative aspects that do not share a natural ordering relationship—or because discretisation allows for better results in the machine learning technique. The research on dataset discretisation for machine learning is vast and beyond the scope of this paper, but it is important to mention that such algorithms usually aim to maximise the interdependency between discrete attribute values and class labels, as this minimises the information loss due to