Local Structural Analysis: a Primer

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Abstract. The structural analysis is a processing step during which graphs are extracted from binary images. We can decompose the structural analysis into local and global approaches. The local approach decomposes the connected components, and the global approach groups them together. This paper deals especially with the local structural analysis. The local structural analysis is employed for different applications like symbol recognition, line drawing interpretation, and character recognition. We propose here a primer on the local structural analysis. First, we propose a general decomposition of the local structural analysis into four steps: object graph extraction, mathematical approximation, high-level object construction, and object graph correction. Then, we present some considerations on the method comparison and combination.

1 Introduction

The problem of document image interpretation is a vast field gathering three main applications: handwriting [58], graphic documents (technical documents [51], maps [43], symbols [32], and so on.), and structured documents [39]. Document image interpretation is an artificial intelligence problem based on three entities: a control system, a pattern recognition process for document images[1], and a knowledge base. Several common works on this problem have been realized during the last fifteen years [12].

This paper deals with the pattern recognition process. Classically, a pattern recognition process is decomposed into two main steps [25]. The first one is an image processing step which has two goals: the image pre-processing allowing to enhance the image's conditions, and the feature extraction for the description of image's shapes. In the following of this paper, as [34], we simply call the feature extraction step "analysis". The second one is the recognition step. This step exploits the extracted features by the analysis step for different purposes like recognition [33], learning [37], indexing [15], data structuring [59], interest zone search [13], and so on. Two main approaches for the pattern recognition process exist: statistical &

[1] In the following, we talk about "recognition process" for "recognition process for document images".

connexionnist [24], and structural & syntactic[2] [53]. This paper deals especially with the structural approach. In this approach, the image-processing step extracts graphs from images and the recognition step exploits them. In these graphs, nodes represent images' objects, and edges represent structural links between these objects. Many different shapes could be described by graphs in document image interpretation such as forms [39], oriental characters [18], and graphic parts [51].

The structural recognition step is a graph exploitation problem, which uses two main approaches: graph-matching [19] and grammar [4]. The first one matches extracted graphs with model graphs. The second one applies different rules to transform extracted graphs into model graphs. A graph problem depends on two criteria: graph/subgraph, and exact-inexact. A subgraph is a subset of node and edge of a larger graph. The subgraph problem is to recognize a model subgraph into a candidate graph. If extracted graphs correspond exactly to model graphs, the problem is known as exact. Unfortunately, in image applications, graphic parts are often connected to other parts, and extracted graphs are noisy and large sized. So, it is an inexact subgraph problem, into candidate graphs of large size.

The analysis step extracts (or constructs) graphs from images. For the purpose of this paper, we simply call it "structural analysis". We can decompose the structural analysis into local and global approaches[3]. The boundary between these two approaches is the connected component. The local approach decomposes a connected component into basic object, and the global approach groups together connected components according to some closeness and connection constraints. The Fig. 1 gives an example of global/local analysis results, with graphic representations and graph visualisations. The local approach (b) decomposes the connected component (a) into arc, junction, and polyline objects. The global approach (c) groups together three connected components (a) according to some neighboring constraints.

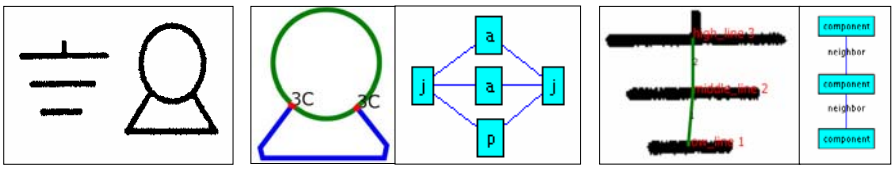

Fig. 1. (a) symbols (b) local structural analysis (c) global structural analysis

This paper especially deals with the local structural analysis. We propose here a primer on the local structural analysis. In section 2, we give a general decomposition of the local structural analysis into four steps. Then, in section 3, we present a comparison study of methods. In section 4, we present some considerations on the method combination. Finally in section 5, we conclude.

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[2] In the following, we talk about "structural" for "structural & syntactic".
[3] This classification also exists in statistical analysis [41].

2 General Decomposition

The local analysis employs different approaches from character recognition (latin [55], oriental [18]), and graphics recognition (technical documents [51], maps [43], symbols [32], and so on.). It extracts different objects from documents according to the exploration granularity. The smallest objects are the pixels and the biggest objects are the connected components. We propose here a general decomposition of the local structural analysis into four steps: object graph extraction, mathematical approximation, high-level object construction, and object graph correction. We present each step in sections 2.1, 2.2, 2.3, and 2.4.

2.1 Object Graph Extraction

This step decomposes the connected component into an object graph. We have listed seven method families as shown in the Fig. 2. The methods are based on skeletonisation (a), contouring (b), tracking (c), run decomposition (d), region decomposition (e), mesh decomposition (f), and object segmentation (g). We present each method family in the next subsections.

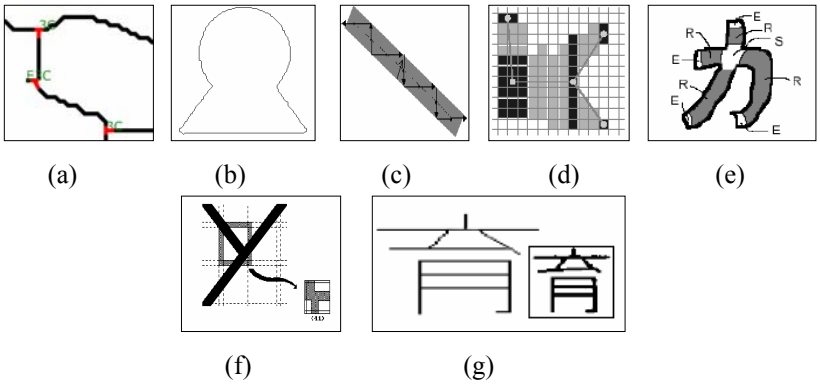

Fig. 2. (a) skeletonisation (b) contouring (c) tracking (d) run decomposition (e) region decomposition (f) mesh decomposition (g) object segmentation

2.1.1 Skeletonisation Based Methods

The skeletonisation based methods are the most commonly used. They involve two steps. The first one extracts the skeleton images [26]. Two main families exist, by distance transform and by iterative thinning [1]. The second one analyses skeleton images in order to extract pixel graphs. In these pixel graphs, nodes represent the skeleton' junctions and chains (pixels lists), and edges represent connection links between these two object types. The junctions detection is based on different methods: the connectivity analysis [54] [44], or the 3-connected pixel destruction [14] [27]. The Fig. 2 (a) gives an example of an extracted pixel graph [14].

2.1.2 Contouring Based Methods

The contouring based methods are often used. Two methods families exist [56]. The first ones use contour images like intermediate representations. They are based on mathematical morphology [20] or on neighbouring tests [14]. Similar to skeletonisation based methods, they involve a second step to extract the contours' pixel chains. The second ones directly extract the contours' pixel chains without any intermediate image representation. They use line following methods [1], or blob coloring methods [14]. Their advantages rely on the fact that they provide the inclusion links between chains, and they permit the selection of internal or external contours [14]. So, it is possible to construct contour graphs in which, nodes represent chains (pixels lists), and edges represent inclusion links between these chains. The Fig. 2 (b) gives an example of external contours' pixel chains of the Fig. 1 [14].

2.1.3 Tracking Based Methods

The tracking based methods directly analyse the images without any intermediate representation. They are based on the structuring elements use in order to track the shapes, of pixel type [16] [48], or area type (circle [11], gaussian bead [61]). They produce pixel graphs [11], or geometric object graphs (arc and vector [48]). In these geometric object graphs, nodes represent geometric objects, and edges connection links between these geometrical objects. The produced graph types depend on the adopted tracking model (linear [16], circular [48]), and on the structuring element's progression into the shape (continuous [11], by jump [16]). The tracking process may be of two types: line tracking and junction tracking. In both cases, the employed structuring element can be of "pixel type" [11] [16], of "area type" [11] [61], or even both [42]. The Fig. 2 (c) gives an example of pixel tracking [16].

2.1.4 Run Decomposition Based Methods

The run decomposition based methods are used for line drawing interpretation [6] and handwriting recognition [17] [60]. A run is a maximal sequence of black pixel in a column or a row of the image. The run graph is constructed with vertical and horizontal runs according to construction rules. In these run graphs, nodes represents runs chains (1-2 connected runs) and run junctions (3-n connected run), and edges represent the connection links between these runs. From this definition, [6] constructs the MRG "Mixed Run Graph", a vertical and horizontal run graph (Fig. 2 (d)). In this MRG, vertical and horizontal runs are merged into junction and line nodes.

2.1.5 Region Decomposition Based Methods

The region decomposition based methods are less used in the literature. They decompose a connected component into different regions in order to construct region graphs. In these region graphs, nodes represent regions, and edges connection links between these regions. [7] [9] compute orientations data of each image's pixel with its contour pixels. Then, they search the majority directions for each pixel, and construct like this the line, extremity, and junction regions (Fig. 2 (e)). In [14], we propose region decomposition method based on a wave aggregation. The wave breaking and stopping cases define the regions' boundaries. In the following step, the region graph is analysed to construct the line or junction regions.

2.1.6 Meshes Decomposition Based Methods

The mesh decomposition based methods have been used for vectorisation applications [29] [57]. Image is firstly split up into meshes. Then, the meshes are recognized according to a mesh library (Fig. 2 (f)) [57]. So, the result mesh map is analysed to construct the mesh graphs. In these mesh graphs, nodes represent the different meshes' objects (vector, arc, symbols, and so on.), and edges the structural links between theses objects (connections, parallelism, and so on.).

2.1.7 Segmented Object Based Methods

The segmented object based methods are often used in vision [38] and in document image interpretation [52]. The segmented object methods directly extract the objects such as lines, arcs, ellipsis, and junctions. These methods employ mathematical transforms in order to change the image's representation space. This representation space is used to find the objects according to their mathematical models. [52] extracts like this the vertical, diagonal, and horizontal lines for Chinese handwriting recognition (Fig. 2 (g)). Some works deal with the junction segmentation [10] ('T' junction, 'X' junction, and so on.), in order to construct geometrical object graphs. Different techniques exist like the Hough transform [38] or the Gabor filters [10]. If the system does not deal with the junction segmentation, the mathematical objects' crossings [36] and the connections between mathematical objects' extremities [52] are searched to construct the structural links between these objects.

2.2 Mathematical Approximation

During this step, the step 1's result objects (graphs' nodes) are approximated by mathematical objects like vectors, arcs, elliptical arcs, and curves (Fig. 1 (a)). The mathematical approximation functions can exploit various entry data like pixels, vectors, curves, and circles. In fact, we can approximate vectors into circles, curves into circles, and so on. The pixel and vector graphs (Fig. 2 (a), (b), (c)) are often used. The region and run graphs (Fig. 2 (d), (e)) are also used after their skeletons and contours extractions [17] [14]. The mesh and segmented object graphs (Fig. 2 (f), (g)) are not used because their objects are enough approximated. So in practice, pixels graphs are the most commonly used for the vectorisation step [31] [54]. An overview and an algorithm permitting a combination of mathematical object approximation can be found in [46]. Also, an algorithm to extract contextual information on the data quality (in order to control a system in the approximation algorithm choice) can be found in [47].

2.3 High-Level Object Construction

After the mathematical approximation step, some systems construct from low-level objects (vectors, arcs, curves) higher level objects like circles, parallelograms, triangles, and so on. These objects are constructed from skeletonisation based process [23] or contouring based process [28] [8] [62] (we talk about contour matching). The contour matching is generally used to rebuild the shapes' junctions [28]. Position

constraints of mathematical objects are tested during this high-level object construction. So, this construction is not only a graph factorisation step. After this construction, new structural representations can be created, describing the structural links between the high-level objects [45]. The Fig. 3 (a) gives a use-case for circle reconstruction from skeletonisation based process [23]. The Fig. 3 (b) gives an example of contour matching into triangle graph [62].

2.4 Object Graph Correction

Some systems analyse the extracted object graphs to correct the structural descriptions. [50] distinguishes systems with corrections (two steps) and without correction (one step). Some corrections add or delete some nodes and edges into object graphs. Other corrections compute new edges or nodes' attributes. These correction processings use image processing steps, so they are not only graph correction processings. These corrections can be used on different data types in (or between) each of steps 1, 2, and 3 (sections 2.1, 2.2, and 2.3).

On the pixel graphs different correction types can be used like pruning and merging [14] (Fig. 3 (c)), and the correction of junctions' distortions [30] (Fig. 3 (d)). These correction methods can be also used on vector graphs [16], but in this case the junction correction by vector crossing search is also used [22] (Fig. 3 (e)). [57] corrects its mesh graphs by a splitting/merging processing. [17] corrects its run graphs with merging/deleting processings of segmented/isolated runs. [45] corrects its high-level object graphs with a merging processing.

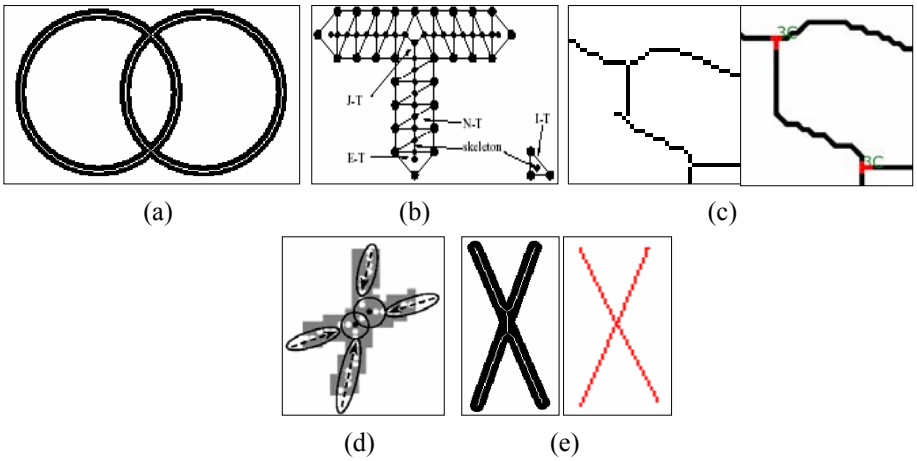

Fig. 3. (a) circle construction case (b) contour matching
(c) (d) skeleton correction (e) vectorial correction

3 Method Comparison

We compare in the Table 1 advantages and drawbacks of the object graph extraction step's methods (section 2.1). The comparisons concerning mathematical approximation step's methods (section 2.2), high-level object construction step's methods (section 2.3), and object graph correction step's methods (section 2.4), that are not detailed in this paper and can be found in [46], [40], and [5]. We compare the object graph extraction methods according to seven criteria which are respectively named "Junction", "Morphology", "Invariance", "Sensitivity", "Semantic", "Reversibility", and "Complexity". "Junction" criterion specifies the methods' ability to detect the shapes' junctions. "Morphology" criterion specifies the methods' ability to analyse heterogeneous shapes. "Invariance" criterion specifies the methods' ability to analyse multiple scales and orientations of shapes. "Sensitivity" criterion specifies the methods' distortion noise resistance. "Semantic" criterion specifies the methods' information adding for the shapes' descriptions. "Reversibility" criterion specifies the methods' ability to restore the raster data. "Complexity" criterion specifies the methods' algorithmic complexity. This comparison study is only based on a set of significant experiments performed in our laboratories [14].

Table 1. method comparison

	Advantages	**Drawbacks**
Skeleton	Invariance	Morphology, Sensitivity, Complexity
Contouring	Morphology, Invariance, Reversibility	Junction
Tracking	Junction, Semantic, Complexity	Morphology
Run	Junction, Morphology, Reversibility	Invariance, Complexity
Region	Junction, Morphology, Reversibility	Semantic, Complexity
Mesh	Junction, Semantic, Complexity	Morphology, Invariance, Sensitivity, Reversibility
Segmentation	Sensitivity, Semantic	Junction, Morphology, Invariance, Reversibility, Complexity

The skeletonisation based methods are invariant [54], but they only permit the linear shape analysis [45], and are noise sensitive (especially for the junction zone analysis [54]).

The contouring based methods permit to analyse all the shape types, and are reversible [20]. Their drawback is the no detection of junctions that must rebuilt with a high-level object construction step [28].

The tracking based methods permit a good junction detection. Beside, they export vectorial data, and are of low complexity [49]. However, they have some difficulties with shapes' thickness variation [42].

The run decomposition based methods [6] permit a good junction detection, any analysis of shape type, and a raster restoration. However, they are sensitive to orientation (because of vertical and horizontal run types) and complex (because of runs encoding and structuring).

The region decomposition based methods also permit a good junction detection, allow to analyse all the shape types, and permit a raster restoration. However, the regions give few information like representation object (analysis must be completed [13] [14]), and have a high memory cost of manipulation.

The mesh decomposition based methods permit a good junction detection, a complex object export, and are of low complexity. However, these methods are very sensitive to the initial positions of considered meshes [57] (invariance, sensitivity) and strongly depend on mesh library / shapes types adequacy.

The segmented object based methods are noise resistant [50], and export geometrical objects [50]. However, the mathematical transforms used are complex [38], based on the known model search [50] (reversible, morphology), limited to some orientations [52] (invariance), and have some difficulties with the junction segmentation [10].

4 Method Combination

Several research perspectives exist on the subject dealing with the local structural analysis. Some works use recognition step in order to control the graphs' constructions with knowledge bases. These controls can be used for all analysis levels and approaches (sections 2.1, 2.2, 2.3, and 2.4) [2] [52] [59] [6]. Other works deal with the segmentation/recognition problem by utilization of "system approaches", like the perceptive approaches [61] for instance, or multi-agent approaches [21]. Finally, some works use strategic approaches in order to combine the methods [14]. We develop this last perspective in this section.

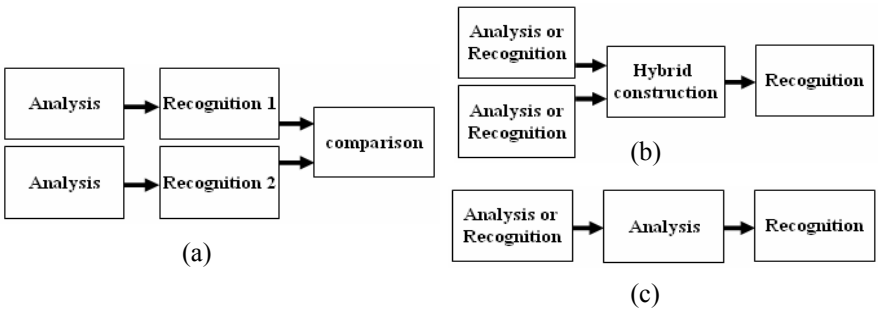

Fig. 4. (a) comparative combination (b) hybrid combination (c) cooperative combination

We propose here a combinations' classification into three categories: comparative, hybrid, and cooperative (Fig. 4). These combinations are essentially local, but some of them deal with the local/global aspects [13] [3]. The comparative combinations (Fig. 4 (a)) analyze the shapes in order to extract different graphs from different methods. These graphs are then compared during the recognition step. [40] compares vector graphs obtained from contour and skeleton images. In [13] we compare loop graphs (global) with skeleton graphs (local). The hybrid combinations (Fig. 4 (b)) analyze the shapes in order to extract hybrid graphs. These graphs are the combinations of two (or several) analysis methods. Besides, the global methods [13] and local [6] [7] [14] exploiting the region objects permit to use a statistico-structural approach [13] [14]. [3] extracts connected component graphs, and completes these graphs with the concavity local information for each connected component. In [13] and [14], we use statistico-structural approaches for the recognition of local/global region graphs. The cooperative combinations (Fig. 4 (c)) exploit the analysis methods in order to simplify the recognition process' complexity. [49] uses an object progressive simplification process. In [13] we simplify our global analysis by the use of a local analysis.

The comparative and hybrid combinations permit the multi-models representations of shapes (or adopted graph model). The multi-model representation's possibilities are obtained by the combinations local, local/global, and statistico-structural. The works on the construction and exploitation of the multi-model representation certainly constitute an important research perspective of the local structural analysis.

5 Conclusion

In this paper, we propose a primer on the local structural analysis. This analysis decomposes the connected components into graph of basic object. Then, these graphs are exploited during the recognition step. This analysis declines itself according to different construction levels, using different methods. Each method presents some advantages and drawbacks. All these methods can be combined, for especially the multi-model representation. These multi-models representations certainly constitute an important research perspective of the local structural analysis.

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