RECOGNITION OF HATCHED CARTOGRAPHIC PATTERNS

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ABSTRACT

This paper deals with the automated interpretation of large-scaled scanned maps, using the example of the german base map *Deutsche Grundkarte 1:5000* (*DGK5*). The goal is a raster-to-vector conversion of the map content. The increasing demand of digital data for building databases in Geographic Information Systems requires the development of powerful techniques to support automated map understanding. The paper presents an approach which automatically detects buildings and separates them from the remaining map objects. In the (mostly) black and white *DGK5* map buildings are represented by their outlines filled with hatched patterns. In contrast to most of the existing approaches for cartographic pattern recognition, a raster based method is proposed. The typical sequences of black and white pixels forming the hatched patterns are used to detect the buildings. The used raster based methods involve the investigation of runlength encoded image rows and columns, a kind of directional region growing and operations of mathematical morphology. It is shown that this map understanding task can be solved in the raster environment up to an advanced processing stage.

KURZFASSUNG

Dieser Artikel befaßt sich mit der automatischen Interpretation von großmaßstäbigen gescannten Karten am Beispiel der Deutschen Grundkarte 1:5000 (*DGK5*). Ziel ist eine Raster-Vektor-Konvertierung des Karteninhalts. Der steigende Bedarf an digitalen Daten für den Aufbau von Datenbasen in Geoinformationssystemen erfordert die Entwicklung leistungsstarker Methoden für das automatische Kartenverstehen. Dieser Aufsatz beschreibt einen Algorithmus, der automatisch Gebäude lokalisiert und sie von den übrigen Kartenobjekten separiert. Gebäude werden in dieser vorwiegend schwarz-weißen Strichkarte durch ihre Umrisse dargestellt, die mit Schraffur gefüllt sind. Im Gegensatz zu den meisten bestehenden Arbeiten im Bereich der kartographischen Mustererkennung wird hier ein rasterbasierter Ansatz vorgeschlagen. Die typischen Abfolgen der schwarzen und weißen Pixel, die die Schraffur bilden, werden für die Detektion der Gebäude genutzt. Die dabei benutzten rasterbasierten Techniken umfassen die Untersuchung von lauflängenkodierten Bildzeilen bzw. -spalten, ein richtungsabhängiges Regionenwachstum und Operationen der Mathematischen Morphologie. Es wird gezeigt, daß die gestellte Mustererkennungsaufgabe bis zu einem fortgeschrittenen Stadium im Raster lösbar ist.

1 INTRODUCTION

1.1 Motivation

The demand of digital information is rapidly increasing due to advanced computer technology and the widespread use of Geographic Information Systems. Each GIS application requests a georeferenced database. Existing paper maps represent such powerful databases. Before they can be integrated in a GIS they have to be converted into a digital vector representation. This is a time-consuming process if it is done by manual digitizing. Scanning maps is a faster way of obtaining digital data. Unfortunately the primary output of the scanning are raster data without any semantic information. Thus raster-to-vector conversion is needed as a first step.

Image understanding algorithms can be used to facilitate and accelerate the raster-to-vector conversion of maps. This task belongs to the broad field of document image recognition which already yields good results for optical character recognition (OCR). Technical drawings such as engineering drawings, graphics and maps, of course, are much more complex than pure alpha-numerical text information. Although some work has already been done in the field of automated map interpretation, e.g. (Illert, 1990), (Kasturi et al., 1990), (Suzuki/Yamada, 1990), (Crosilla/Piccinini, 1991), (Antoine/Collin/Tombre, 1992), (Boatto et al., 1992), (Hori/Okazaki, 1992), (Ablameyko et al., 1993), (Ebi, 1993), (Yamada/Yamamoto, 1993), (Mayer, 1994), operational systems interpreting complex maps in satisfying quality are still rare.

The presented work deals with map interpretation using image understanding algorithms aiming at automatic raster-to-vector conversion. Because of the high complexity of map graphics, the automated interpretation of the map as a whole document is not possible at the current stage of technology. Thus the presented work is focused on *buildings*. Spatial information about buildings are needed in many fields such as regional planning or 3D modelling of urban areas. Furthermore, digital vector data representing the shape of buildings can be used as apriori-knowledge to support automated analysis of actual aerial photographs for change detection and map updating as it is, for instance, shown by (Quint/Bähr, 1994), (Quint/Sties, 1995).

1.2 Data Source

As data source the *Deutsche Grundkarte 1:5000 (DGK5)* is used which is the primary topographic map of Germany covering at least 80% of the country. The *DGK5* represents the topography as brown contours and all other objects as black lines and symbols. The map objects are determined by their shape, linewidth and relativ position. Fig.1a shows a subset (~60 by 75 metres in reality) of a scanned *DGK5*.

This type of map was chosen for the following reasons: Due to its large scale the objects remain true to scale and shape. The mapped buildings are characterized by a high positional accuracy ranging from 0.1 to 0.3 meters. Furthermore, the data are more complete (every building covering more than 15 m^2 is mapped) and more actual than German cadastral maps which merely contain 70% of all existing buildings whereas in the *DGK5* 95% of all existing houses are included.

In the *DGK5* a building is represented by its outline filled with a hatched pattern, an optional house number and, in few cases some additional explanatory characters. The hatched pattern consists of parallel and equidistant straight lines. The types of buildings are characterized by different hatched patterns varying in the slope of the hatching line with respect to the longer edge of the building. Residential buildings are marked by diagonal hatching lines (angle of 45°) whereas outbuildings like garages are depicted with parallel hatching lines (angle of 90°), see Fig.1.

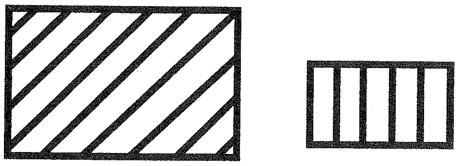


Figure 1: Different Types of Buildings of the *DGK5*

However, a robust recognition of these objects is difficult because the objects have manifold shapes reaching from simple single rectangles to complex building agglomerations in city centres. In addition, the hatched patterns can occur in any direction and a wide range of spatial extensions, whereas irregularities often arise. The most common irregularities are broken hatching lines because of overlaying of other cartographic objects, widened cross points at merging areas of hatching lines with corners or edges of the building-outlines, interrupted lines, varying equidistances of hatching lines and non-parallelism.

2 OUTLINE OF THE NEW RASTER BASED APPROACH

Existing approaches of automated map interpretation, e.g. (Illert, 1990), (Hori/Okazaki, 1992), (Ablameyko et al., 1993), (Mayer, 1994), mostly start with a vectorization of the entire image content and only as a second step, they try to find structures representing map objects. Vectorization at this early processing stage always leads to a loss of original information. These problems are caused by steps like thinning, distance transformation and skeletonisation. As a result, errors in position or topology occur (Klauer, 1993). Another disadvantage of this approach is the large amount of obtained vector data which is difficult to handle during the various processing steps.

In contrast, this paper describes a new method for hatched building recognition using *raster based* techniques until an advanced recognition stage.

The developed approach suits the following main principles: At the beginning hatched patterns only serve as characteristic features to locate buildings and separate them from the remaining map objects. For that purpose the spatial extension of hatching is recognized in the raster environment.

In a second step the identified hatched patterns are removed so that only the building-outlines remain in form of a raster representation. This way the following vectorization process only deals with the empty outlines of the buildings.

The hatching is eliminated because it carries no additional information to identify the location of the buildings. Furthermore, the hatching introduces 'noise' in the vectorization process and causes an unnecessary large amount of vector data.

For the described recognition task different raster based techniques are combined. Since mathematical morphology is one of the most important ones, the following section gives a brief introduction to this method. After that, the developed raster based approach is explained and first results are shown.

3 MATHEMATICAL MORPHOLOGY

Mathematical morphology is the name of a specific collection of set theoretic operators defined on an infinite lattice, see e.g. (Haralick/Shapiro, 1992). These operators, which were first examined systematically by (Matheron, 1975) and (Serra, 1982) in the 1960's are an extension of Minkowsky's set theory. The operators are especially useful for image analysis and image enhancement. They represent an interesting alternative to classical linear filter convolutions. In contrast to the classical ones, the morphological operators are shape-dependent and nonlinear image transforms. They can be defined in binary or grayscale images for any number of dimensions. Since the presented work is based on binary images, the following explanations are limited to the topic of *binary* mathematical morphology.

A morphological operator is governed by a small pseudo image, a so called *structuring element*. When applied to an image, the operator returns a quantitative measure of the image's geometrical structure in terms of the structuring element. This measure can be used to decompose complex shapes into their meaningful parts and separate them from their extraneous parts.

The primary morphological operations are erosion and dilation. The erosion — as its name already indicates — removes pixels from border areas in the foreground region. In contrast, the dilation adds pixels to border areas. The extent to which the original shapes of the image are changed, depends on the shape of the structuring element. The structuring element is an operator mask of any shape. Frequently used structuring elements are e.g. disk shaped masks.

The erosion follows the principle: If all pixels of a foreground region in the original image I are covered by the structuring element S, the considered central pixel will be set to 1 (foreground) in the resulting image. The erosion operation is denoted by $I \ominus S$.

Dilation, denoted by $I \oplus S$, is the morphological opposite of erosion: In case the structuring element covers at least one pixel of a foreground area in the original image, the actual pixel will be set to 1.

On the base of dilation and erosion the morphological operations of opening and closing can be composed. Opening consists of an erosion followed by a dilation: $I \circ S = (I \ominus S) \oplus S$. Vice versa closing is a dilation followed by an erosion: $I \bullet S = (I \oplus S) \ominus S$. Opening mainly leads to smoothing of fringed borders and the elimination of small areas. Closing can be

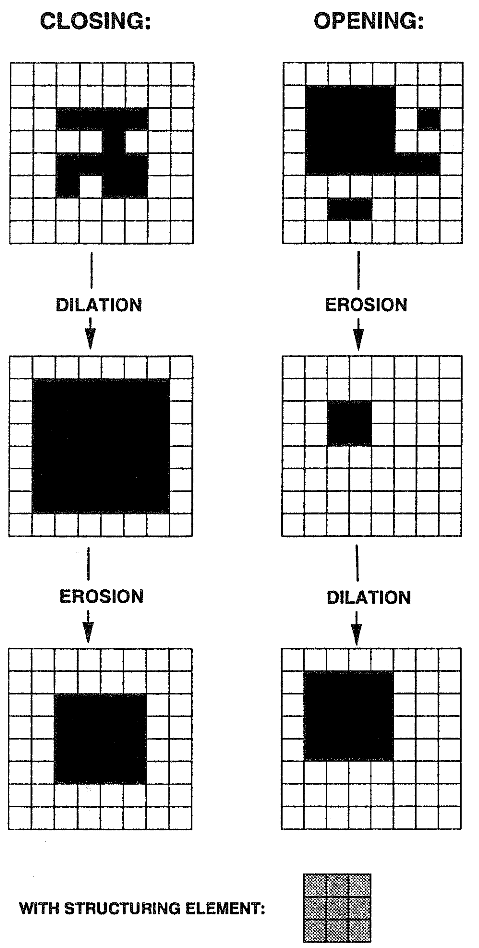


Figure 2: Mathematical Morphology Operators

useful to fill little gaps between border fringes (Fig. 2).

4 DEVELOPED APPROACH AND RESULTS

In this paper we concentrate on the first location step, the detection of hatched areas of the map in the raster environment. For fulfilling the introduced pattern recognition task it is important to choose rotational invariant features taking into account all possible orientations of the hatched patterns. For that reason simple template matching methods, as e.g. (Stengele, 1995) uses for the recognition of characters and symbols in a swiss topographic map 1:25000, have to be ruled out because they would require the laborious rotation of the templates in multiple directions.

An eyecatching feature of hatched patterns is their typical periodical sequence of black and white pixels with an approximate constant ratio between the numbers of successive black and white pixels. This striking feature is used in the recognition process.

A subset of the scanned *DGK5* sheet *'Karlsruhe Weststadt'* has been chosen (see Fig. 6a) to demonstrate the results of the developed raster based approach on a real map example. The subset was scanned with a resolution of 450 dpi and contains approximately 200 × 300 pixels. A threshold operation was applied to transform the scanned map data, originally ranging of 255 grayvalues, into a binary image.

The subset represents a residential neighbourhood which is typical for areas close to city centres in Germany. It includes residential buildings, outbuildings, and property boundaries surrounding courtyards, as well as landuse type boundaries marking streets and pavement, characters and symbols depicting single trees and cross points of boundaries.

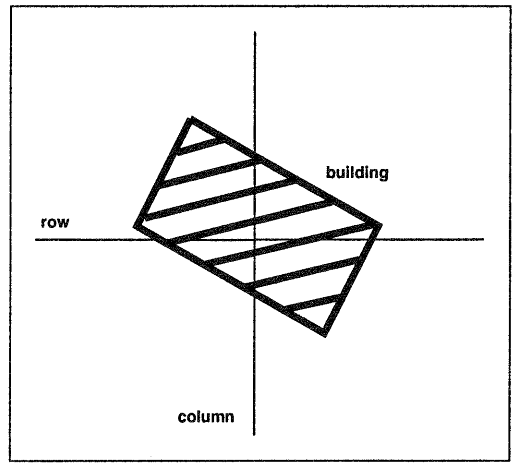


Figure 3: Directions of Runlength Vector Analysis

4.1 Detection of Hatched Areas

The developed approach is based on the analysis of runlength encoded image rows and columns and resembles, in this first step, an approach of (Shen/Ebi/Besslich, 1991). In this connection, the analysis of the 2-dimensional image lattice is split up into the analysis of two 1-dimensional signal vectors (see Fig. 3). A runlength encoded vector $\boldsymbol{r} = (r_1, r_2, ..., r_k)^{\top}$ contains the number r_i of successive black and white pixels, respectively.

Figure 4: Part of an Image Row

The runlength encoded vector to the example of Fig.4, for instance, reads as $\boldsymbol{r} = (3,\ 5,\ 3,\ 6,\ 4)^{\top}$.

These runlength encoded rows and columns have to be searched for areas which contain hatched patterns to cut them out of the original image. For that purpose a so called *hatching-factor* h has been created denoting the ratio between width of the hatching line and width of the space between hatching lines. This factor h is rotational invariant because of the well-known relations between similar triangles. The only problem are hatching lines having the same direction as the runlength-vector $\boldsymbol{r}$. To handle such cases, at least one second direction has to be investigated, whereas more than one additional direction would probably lead to more robust results.

Subvectors $\tilde{\boldsymbol{r}}$ containing 4 successive elements of the runlength encoded vectors $\boldsymbol{r}$ and representing the minimum number of hatching lines defining a *hatched pattern*, are examined in sequentially moving ahead run by run.

$$\tilde{\boldsymbol{r}} = (r_i,\ r_{i+1},\ r_{i+2},\ r_{i+3})^{\top}\ ,\quad i = 1, ..., k-1\ . \qquad (1)$$

With

$$\begin{aligned} (r_i,\ r_{i+2})^{\top} &= (b_1,\ b_2)^{\top} = \text{black pixel runs} \quad (2)\\ (r_{i+1},\ r_{i+3})^{\top} &= (w_1,\ w_2)^{\top} = \text{white pixel runs} \quad (3) \end{aligned}$$

or vice versa. The above described hatching factor reads as

$$h = \frac{b_1 + b_2}{w_1 + w_2} \tag{4}$$

The determination of hatched areas takes into account the following conditions:

$$|b_1 + b_2| < T_b \quad \text{and} \quad |w_1 + w_2| < T_w \tag{5}$$

$$T_l < h < T_u \tag{6}$$

with T_b, T_w, T_l and T_u being empirically fixed thresholds. The latter condition allows little variations within the amount of the hatching factor which are caused by non-parallelism, non-equidistances and varying linewidths. These rules (5) are not valid for areas with a fitting hatching factor but false dimensions of black and white runs with respect to hatched patterns.

The resulting images I_r and I_c of this analysis of the run-length encoded image rows and columns (Fig. 6b and 6c) show that all hatched areas have roughly been detected. Those areas which have not been recognized by the row analysis, appear for that in the result of the column analysis. Both kinds of hatched patterns have correctly been found and most of the other cartographic objects like boundaries and symbols have been eliminated. Of course, undesirable small areas of disturbances appear and the borders of buildings show ugly fringes. The approach fails, if the numbering of the houses interrupts the regularity of the hatching lines. For these reasons further improvement of the approach is required.

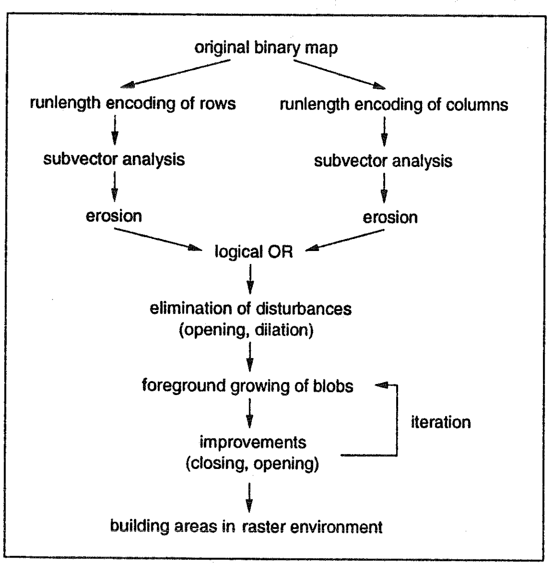


Figure 5: Flow Chart of Building Detection Process

4.2 Elimination of Disturbances

Aiming at elimination of small disturbances which are mostly false classifications due to hatching-like structures, the two partial results I_r and I_c have been eroded with a disk shaped structuring element S_5 with bounding box of 5 × 5 pixels:

$$I_{r2} = I_r \ominus S_5 \ , \ I_{c2} = I_c \ominus S_5 \tag{7}$$

Afterwards the two images I_{r2} and I_{c2} have been overlayed with a logical 'or' to get all hatched areas into a single image I with

$$I = I_{r2} \vee I_{c2} \ . \tag{8}$$

Fig.6d shows the result. Most of the disturbances are disappeared, but borders of the buildings do not appear in a satisfying quality yet, also the numbers of the houses are missing. However, the structure of buildings grouped along the streets can already be discerned. An opening with the same disk shaped structuring element as described above was applied to eliminate remaining small errors and smooth the borders of the buildings.

$$I_1 = I \circ S_5 = (I \ominus S_5) \oplus S_5 \tag{9}$$

Because the so called *'blobs'* denoting the extracted shapes of the buildings are still smaller than the original shapes, a dilation is carried out:

$$I_2 = I_1 \oplus S_5 \tag{10}$$

Numbers of houses and borders are still missing, but little gaps are closed and the blob shapes correspond better to the original shapes of the houses. (see Fig. 6e).

4.3 Foreground Growing of Blobs

At that point, the blobs have to be expanded to the outlines of the buildings. This is done based on the knowledge that buildings have a closed border of black foreground pixels. For that purpose the transition from the blobs to the grey background is examined using the original image. The analysis is carried out in 4 different directions: western, eastern, northern and southern. Moving from the inner part of the blob to its border, the first following pixel of the grey background is investigated. If this pixel is black in the original image, the blob will be expanded to that pixel. This process is iterated until the first white pixel in the original image has been reached. This way the blobs are growing, but only in regard to the black pixels of the original image (see resulting image I_3 in Fig. 6f).

Most of the borders and even of the numbers of the houses can be reconstructed by this method. With respect to the numbers it has to be pointed out that it only works if the numbers touch a hatching line. Furthermore not all gaps have been closed, and the expansion of the blobs also happens in undesired areas, such as boundaries.

4.4 Improvements

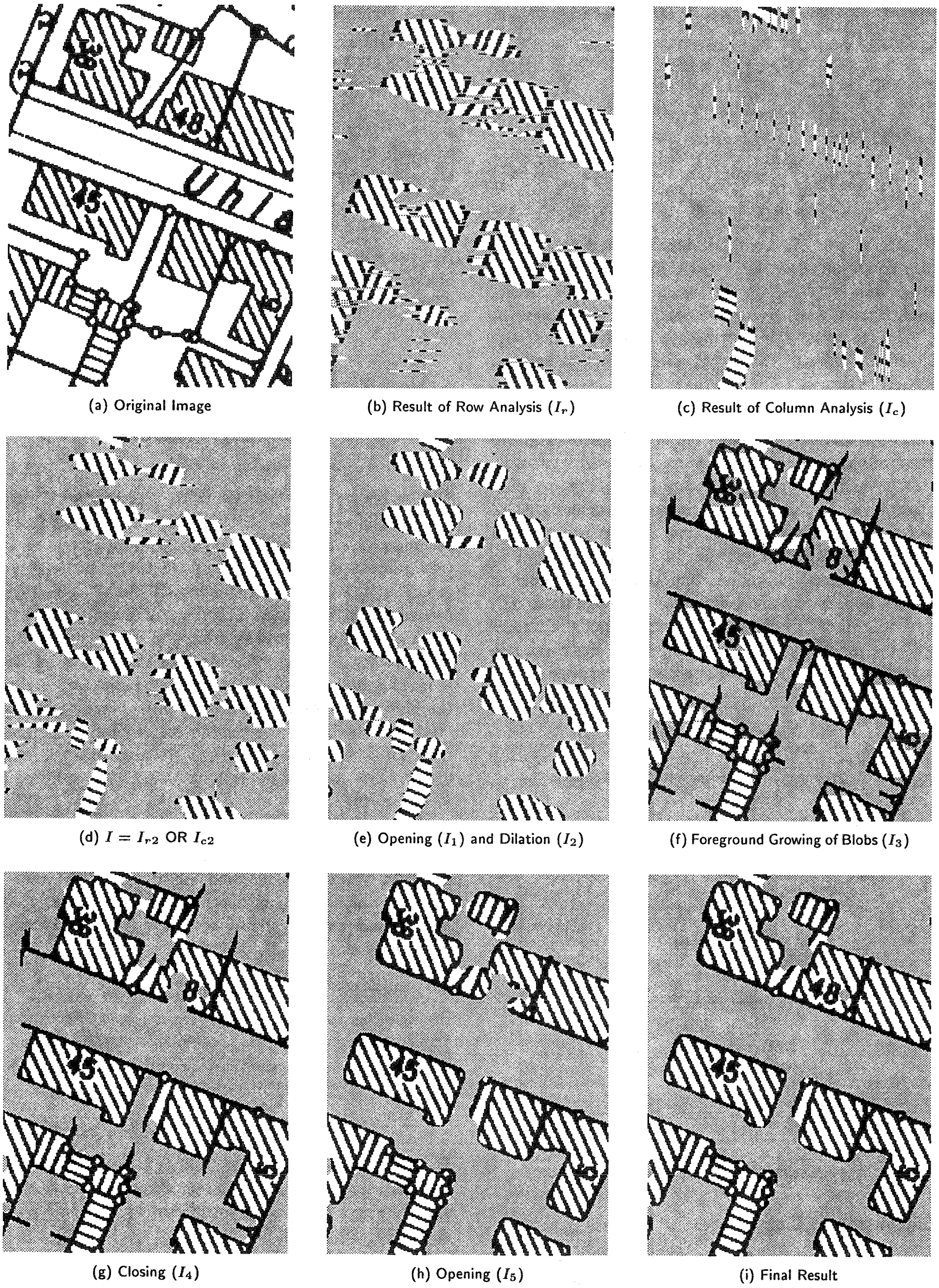
Because the precedent blob expansion only affects the black pixels, gaps remain within the blobs. These blobs can easily be closed by a closing operation with a slightly larger disk shaped structuring element (with bounding box of 7 × 7 pixels):

$$I_4 = I_3 \bullet S_7 = (I_3 \oplus S_7) \ominus S_7 \tag{11}$$

Fig. 6g illustrates that almost all gaps are closed. After that the disturbing fringes can be eliminated by an opening operation with a relatively large structuring element (bounding box of 13 × 13 pixels):

$$I_5 = I_4 \circ S_{13} = (I_4 \ominus S_{13}) \oplus S_{13} \tag{12}$$

The result is to be seen in Fig. 6h. At the current stage of the process the shapes of the blobs correspond well to the real building shapes. Only one house number has been lost. Repeating the foreground growing step up to this point yields a slight improvement. Fig. 6i demonstrates the final result. Critical areas are hatching-like structures which e.g. appear at boundaries between neighbouring but not adjacent buildings.



(a) Original Image (b) Result of Row Analysis (I_r) (c) Result of Column Analysis (I_c)

(d) $I = I_{r2}$ OR I_{c2} (e) Opening (I_1) and Dilation (I_2) (f) Foreground Growing of Blobs (I_3)

(g) Closing (I_4) (h) Opening (I_5) (i) Final Result

Figure 6: Steps of Raster Based Approach

4.5 Further Steps

Future analyzing of the type of hatched patterns (diagonal or parallel) will enable the determination of the use of buildings (residential buildings or outbuildings) besides the pure location information.

Further steps will be the elimination of remaining errors as well as the hatching lines. This way the final vectorization only will have to deal with the empty outlines of the buildings.

Concerning the building outlines, it is planned not only to extract the outer boundaries (transition of blobs to background) but also to extract the inner boundaries between adjacent houses. However, the latter task will be more complicated.

Furthermore, the addition of two more analysis directions, the diagonals, in terms of the investigation of the runlength encoded vectors is planned. That will probably reduce ambiguities and make the results more robust.

Additionally, it has to be thought of relating the empirically found dimensions of the structuring elements to the scanning resolution and to different line widths. Possibilities of including algorithms for assessing the obtained results should be included.

5 CONCLUSIONS

The paper demonstrates a procedure for a raster based, automated recognition process of buildings within the german base map 1:5000. The identification of the buildings includes the recognition of the hatched filling patterns as well as the outlines of the buildings. Although the results represent a preliminary stage, they show the general potential of *raster based* techniques, such as mathematical morphology, for automated map understanding tasks.

The advantages of the introduced *raster based* approach can be summarized in the following way:
- low complexity of the approach
- maintenance of the positional accuracy because of the acting on the original image data up to an advanced processing stage
- strongly reduced amount of vector data.

Since an enormous amount of digital building data has to be captured, e.g. for the creation of 3D models of towns, the proposed approach is a useful tool to obtain the 2D outlines of buildings as vector representations in an efficient way.

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