

# A Survey of Digital Map Processing Techniques

YAO-YI CHIANG, University of Southern California

STEFAN LEYK, University of Colorado, Boulder

CRAIG A. KNOBLOCK, University of Southern California

Maps depict the natural and human-induced changes on earth at a fine resolution for large areas and over long periods of time. In addition, maps – especially historical maps – are often the only information source about the earth as surveyed using geodetic techniques. In order to preserve these unique documents, increasing numbers of digital map archives have been established driven by advances in software and hardware technologies. Since the early 80s, researchers from a variety of disciplines including computer science and geography have been working on computational methods for the extraction and recognition of geographic features from archived images of maps (digital map processing). The typical result from map processing is geographic information that can be used in spatial and spatiotemporal analyses in a Geographic Information System environment, which benefits numerous research fields in the spatial, social, environmental, and health sciences. However, map-processing literature is spread across a broad range of disciplines in which maps are included as a special type of image. This article presents an overview of existing map processing techniques with the goal of bringing together the past and current research efforts in this interdisciplinary field, to characterize the advances that have been made, and to identify future research directions and opportunities.

Categories and Subject Descriptors: **A.1 [Introduction and Survey]; H.2.8 [Database Management][Database Applications]**: Spatial Databases and GIS

General Terms: Design, Algorithms

Additional Key Words and Phrases: map processing, geographic information system, image processing, pattern recognition, graphics recognition, color segmentation

## 1. INTRODUCTION

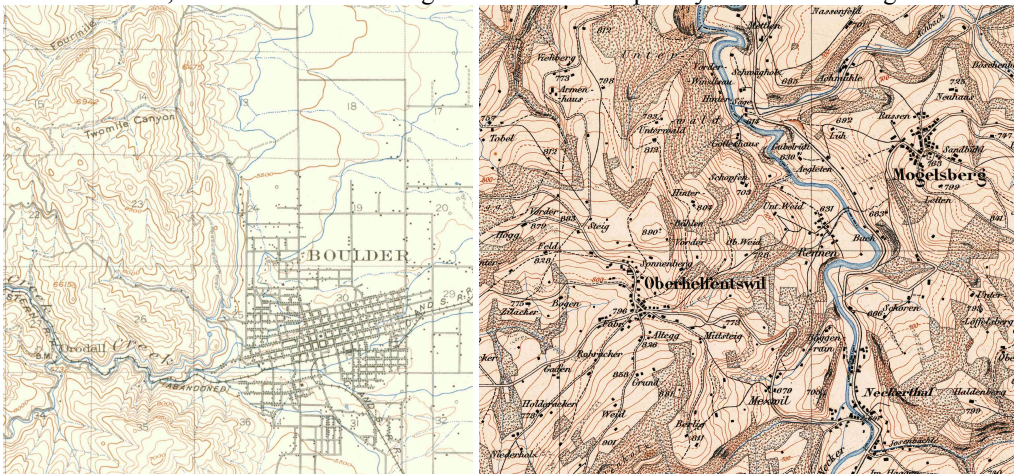
This article presents an overview of the techniques for “digital map processing” (or simply “map processing”), which refers to computational procedures aimed at the automatic or semi-automatic extraction and/or recognition of geographic features contained in images (usually scanned) of maps. Digital map processing is a relatively young research field that grew out of image processing, document analysis, graphics recognition, and digital cartography. Over the past 40 years, researchers have become increasingly interested in the methodological aspects of computational map processing (mostly in scanned maps) for the purposes of retrieval, extraction, and integration of geographic data (Freeman and Pieroni, 1982). This increasing attention results not only from the parallel advances in technologies (e.g., digital image analysis, recognition, and Geographic Information Systems (GIS)), but also can certainly be linked to the fact that computational map processing methods enable the preservation of unique (historical) maps and the utilization of the contained geographic information in modern analytical environments (e.g., in a GIS).

Maps can cover large areas over long periods of time for many regions in the world. This makes maps unique documents witnessing places, human activities, and natural features in the past for which no or only limited alternative information sources exist. Processing map images to extract and recognize geographic information results in spatially referenced data (i.e., map data) that can then be accessed, processed, and maintained in a GIS environment (in other words, “unlocking” geographic information from map documents). Incorporating map data into a GIS environment (i.e., map data can be used for spatial analyses and overlaid with other spatial data) creates unprecedented opportunities for multi-temporal and multi-contextual spatial analyses such as analyzing the changes in built-up areas over large regions across long time periods and investigating how these changes interact with other geographic features such as vegetation or wetland areas. In addition, digital map processing can expedite the processes of comparing map contents from different map series/editions (e.g., contemporary maps vs. historical maps), to update current map series, and to create thematic maps or new map series.

The need for computational solutions with higher degrees of automation for map processing becomes evident if one considers that millions of map documents have already been scanned and stored in digital archives. For example, the U.S. Geological Survey (USGS) continues to scan and release all editions of more than 200,000 historic topographic map pages of the United States that cover the time period of 1884 – 2006. The GIS Center in Academia Sinica, Taiwan, has scanned and archived more than 160,000 historical maps. Such digital archives can only be fully used after

the archived maps have been converted to a GIS usable format. However, manually processing these maps not only generates non-reproducible data that can suffer from a high degree of inaccuracy and introduced subjectivity, but also does not scale well for handling large numbers of maps. For example, manually digitizing one sounding label on a nautical chart includes two steps: drawing a minimum bounding box to label the sounding location and typing in the sounding value. If these two steps take a total of six seconds per sounding label, for a typical nautical chart that has more than 4,000 sounding labels, the digitization process takes more than six hours. In contrast, using digital map processing techniques can dramatically reduce the time (and cost) to fully utilize the geographic information locked in these maps. For example, Chiang and Knoblock (2011) developed a map processing package, Strabo, which only requires one minute of the user's time for operating the software to recognize 1,253 labels from an area in a nautical chart with 83% precision and 80% recall. For this particular area in the nautical chart, the amount of user time for verifying and correcting the recognition results from Strabo is under one hour, which is around 30% of the time that would be needed when performing the entire text recognition task manually. Without such computational solutions for map processing, large portions of the spatial data in maps remain inaccessible unless they are manually converting to spatial datasets.

General techniques for document analysis and graphics recognition (e.g., Cordella and Vento, 2000; Lladós et al., 2002) cannot be directly applied to map processing because maps often pose particular difficulties for recognition due to various graphical quality issues and the complexity of the map contents. The graphical quality of scanned maps can be affected by scanning or image compression processes. In addition, the stored and archived map materials suffer from aging and bleaching effects while original reproduction materials (e.g., copper plates) have often been destroyed or lost. The final scanned images inherit these graphical properties. Figure 1 shows examples of two scanned historical maps of inferior graphical quality due to the imperfections (including manually drawn features) of the original maps. Furthermore, as seen in the sample map in Figure 2, layers of geographic features, such as roads, contour lines, and labels, often overlap with each other, which increases the degree of content complexity and color mixing.



**Figure 1** Subsections of two examples of scanned (historical) maps of inferior graphical quality due to aging and bleaching effects: USGS topographic map of Boulder, CO (1902) at a scale of 1:62,500 (left), and Swiss National Topographic map (Siegfried map), page 220, Brunnadern (1879) at a scale of 1:25,000<sup>1</sup>

Various types of maps have been produced manually until recently (e.g., using copper plate or stone engraving techniques) resulting in high variations of symbol appearances and colors occurring on papers and in the final scans. Graphical guidelines for maps are often map specific and rule-based but usually do not satisfy the quality requirements for machine drawings most often described and processed in document analysis and recognition work. This impedes processing map images within a general document recognition framework. For example, state-of-the-art commercial optical character recognition (OCR) tools can achieve high recognition rates in documents containing text lines of the same orientation, but recognizing map labels (text) in

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have drawn on our combined 30 years of research experience on map processing to select and present the most important and promising techniques.

The remainder of this survey is organized as follows. Section 2 outlines a brief history of map processing research and defines the scope of this survey. Section 3 describes the relevant basic techniques in document analysis and pattern recognition that support map processing. Section 4 reviews past and ongoing research on map processing for extracting and recognizing geographic information from scanned maps. Section 5 concludes with a discussion and directions for future work.

## **2. A BRIEF HISTORY OF MAP PROCESSING AND THE SCOPE OF THIS SURVEY**

Efforts of map processing or information extraction from maps have been going on for four decades (Freeman and Pieroni, 1982) and show an increasing intensity as scanning technologies improved, storage capabilities increased, and processing speed increased. Research on map processing has been conducted on different types of maps including cadastral or land register maps (e.g., Boatto et al., 1992; Di Zenzo et al., 1996; Katona and Hudra, 1999; Raveaux et al., 2008), road maps (e.g., Bin and Cheong, 1998; Itonaga et al., 2003; Dhar and Chanda, 2006; Bucha et al., 2007; Chiang et al., 2009; Chiang and Knoblock, 2013), hydrographic maps (e.g., Trier et al., 1997), city maps (e.g., Chen et al., 1999), utility maps (e.g., den Hartog et al., 1996), as well as topographic or other survey maps (e.g., Morse, 1969; Yamada et al., 1993; Yamamoto et al., 1993; Khotanzad and Zink, 1996; Frischknecht and Kanani, 1998; Arrighi and Soille, 1999; Ogier et al., 2001; Bessaid et al., 2003; Miyoshi et al., 2004; Chen et al., 2006; Leyk et al., 2006; Xin et al., 2006; Henderson et al., 2009). Mostly, the described systems were unable to process different types of maps and so the focus was rather narrow (e.g., extraction of geographic feature layers from USGS Topographic Maps (Henderson et al., 2009)). Most studies focus on particular features, symbols, or map layers and thus efforts to extract map contents have been highly map specific, not applicable to a broader range of map products.

One important question that becomes apparent is: why is the literature on map processing so dispersed over various scientific disciplines? This question can be answered by looking at the early years of map processing when this research direction was considered part of image or document analysis. At that time the main actors were computer scientists interested in technological aspects around digitization and information extraction in general; they developed specific hardware for manual map digitization (Leberl and Olson, 1982), and they considered maps as just one kind of document (Cofer and Tou, 1972; Ejiri et al., 1984) without exploiting many of the cartographic principles to process maps. As soon as the first GIS tools became more established and available as desktop solutions, the interest in digital map data and recognition tools increased considerably. GIS users, companies, and institutions quickly realized that maps in analog (paper) format represented one important source for generating digital spatial information that could be accessed, stored, and managed in GIS environments. Naturally, the issue of recognition in map documents gained more interest in the scientific community for two main reasons. First, the large number of paper maps stored in archives called for the need of higher degrees of automation since manual digitization was (and is) a highly labor-intensive, expensive process. Second, it was soon realized that such extracted spatial data would enable unprecedented GIS-based research efforts in a variety of disciplines such as landscape ecology (e.g., Kienast, 1993) or land-cover change analysis (e.g., Petit and Lambin, 2002; Kozak et al., 2007) as well as in studies on population dynamics and urbanization (e.g., Dietzel et al., 2005), potentially covering large areas and long periods of time. Thus the growing interest in map processing is driven by the increasing topical or substantive potential to use map data and also by the lack of general methods and techniques to overcome the technological challenges in map processing.

Nowadays, map production in the Western world is mainly digital and thus map processing focuses primarily on historical map documents (historical in a sense of predating the switch to digital map production), which were originally published on paper. In addition, map processing also focuses on map documents of which the original reproduction materials do not exist or are difficult to access. Thus the motivation of map processing is twofold: on one side, the scanning, digitization, registration, and referencing of maps represent an important way to preserve existing paper maps in a digital format. On the other side, map processing aims at the generation of spatial data that can be used in a GIS for spatial analyses and can be combined with different spatial data

from various points in time. As such, map processing can also be seen as an advanced approach to derive and preserve unique historical information that provides a way to generate a better understanding of the complex landscape and its changes over long time periods.

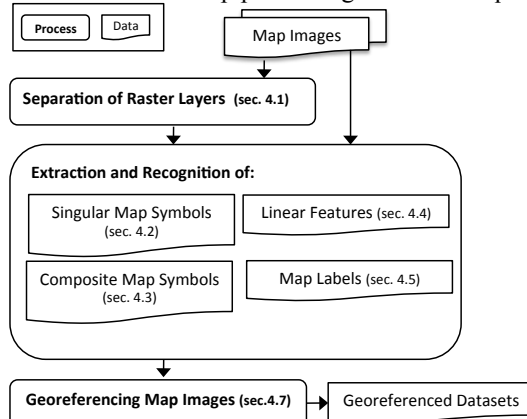
Maps are widely used in our daily life, and for centuries cartographers have been producing maps. In this survey, we focus on the map processing techniques that process map images underlying common cartographic principles and leave out other types of maps that would require different processing techniques for information extraction; two examples are sketch maps (Broelemann and Jiang, 2011) and tourist maps, which commonly do not have an underlying map projection and are intentionally biased or skewed to improve information representation. Since map processing is an active research area that spans many research fields such as geography, pattern recognition, computer vision, image processing, and document analysis and recognition, the terminology used can be slightly different depending on the publication venue. Therefore, below the terminology used in this survey is briefly defined:

- A *scanned* map is a digital image of a paper map generated using an image scanner. For example, the USGS digital raster graphics is a series of scanned maps from the USGS standard topographic map series.
- An *electronic* map is an image of a map generated directly from computer systems, in most cases, GIS. Electronic maps represent a large portion of map images on the Internet (where maps can be found by keyword search using search engines (Goel et al., 2011)), such as snapshots of Google Maps or copies of the TIGER/Line maps. The source and georeferencing information of these map images is often missing or unknown, and digital map processing techniques can be used to georeference the maps (Chen et al., 2008; Chiang et al., 2009) or identify the map source (Chiang and Knoblock, 2009).
- A *map image* is either a scanned map or an electronic map.
- *Digitizing or digital encoding* a map is the process of converting a map image into spatial datasets (i.e., points, lines, and polygons in vector format or extracted layers in image (raster) format). For example, the result from map digitizing can be any of the commonly available spatial vector data types (e.g., Esri shapefiles) where linked nodes and vertices can be used to represent features such as road lines.
- A *geographic feature* or *map feature* can be a set of linear objects, such as road lines or contour lines, a set of character objects, a set of area objects (area features), or a set of map symbols.
- A *geographic-feature layer* (feature layer or map layer) is a bi-level image that contains a number of pixels representing a set of geographic features in a map.
- *Extracting* a geographic-feature layer or a geographic feature is the process of extracting the set of pixels that represents an individual geographic feature in a map.
- *Recognizing* a geographic feature is the process of converting the geographic feature into a machine-editable format, such as a road vectorization process in which the recognized data are of known semantic meaning.
- An *attribute* is a characteristic that can be used to characterize features (e.g., shape descriptors) or colors (color attributes). The term “feature” is often used for “attribute” in the image processing and computer vision literatures. However, for the purpose of consistency in this survey we use feature as described above and strictly rely on the term “attribute” for characteristics or descriptors of such features and/or colors.

### 3. BASIC TECHNIQUES FOR DOCUMENT ANALYSIS AND PATTERN RECOGNITION IN MAP PROCESSING TASKS

The overall goal of map processing is to generate either image (raster) or vector layers of geographic features from map images for subsequent use in a GIS. One common way to reach this goal is to first separate geographic feature layers from map images by grouping image pixels of similar colors. An image (raster) layer can then be converted to vector data by recognizing individual features of a geographic type from each of the separate layers. Other approaches compute (geometric) attributes (e.g., shape descriptors) from training samples of desired geographic features and search for similar patterns in the map to directly recognize individual geographic features. Figure 3 shows a typical workflow for map processing where each process

maps to a subsection in this survey. The entire workflow can be fully automatic, require some pre-processing/post-processing, or interactive (Section 4.6). In the remainder of this section, we briefly describe the background knowledge of printing and scanning techniques and then introduce the basic techniques of color image segmentation and feature recognition that are relevant for map processing. These technical details will lay the foundation for then reviewing the different contributions on map processing in the subsequent sections of this survey.



**Figure 3** An example map processing workflow and the corresponding sections in this survey

Before any of these techniques can be applied to map documents, which are in general printed on paper, these documents have to be scanned. This scanning process is a crucial step to produce map images and determines the image quality of the scanned maps. Scanning parameters such as spatial sampling rate (or resolution), sampling spot size (or blur), bit depth of the resulting data, brightness and contrast settings, as well as scanner calibration procedures, are determinants of the properties of the resultant image and subsequent extraction techniques heavily depend on these properties. One of the most important parameters on a consumer grade scanner is the scanning resolution. A rule of thumb is that for OCR, the scanning resolution needs to be at least 300 dot-per-inch (DPI). Figure 4<sup>3</sup> demonstrates two sets of maps scanned with three different scanning resolutions.

While a quantitative measurement of the scanning quality is possible (e.g., using signal-to-noise ratio to compare multiple scans of the same images), judging the quality of a scanned map for its suitability for digital map processing is subjective and can vary among different geographic features. Figure 5 shows the same map scanned from two different materials (paper types). For the purpose of contour line extraction, the scanning results on the left of Figure 5, which originate from plasticized paper, are favorable since the contour lines appear crisp in the final image. On the other hand, for the purpose of character recognition, the scanning results from plain paper (on the right of Figure 5) are more suitable due to the solid, uniform-colored characters. In this survey we do not include specifics of the scanning process and focus on the map processing techniques (see Stoffel and Moreland (1981) and Sharma and Trussell (1997) for more details on image scanning and digital color imaging). Additionally, the printing method used for map production and materials of the original maps largely affects the results of the final scans. For example, maps were often printed using a halftoning process, which uses limited colors to create a uniform perception of numerous color tones. A typical result from the halftoning process is a series of dotted pixel patterns (texture) in the scanned image. The green and blue areas in Figure 4 show these dotted patterns. Noise removal filters, such as the median filter, are usually applied to the raw scanned image before the color segmentation step to suppress the halftone texture (Fung and Parker, 1996).

A common image format to store the raster image (bitmap) produced from scanning is the TIFF (Tagged Image File Format). The TIFF is a flexible format that supports both lossy and lossless compression methods, various image types (e.g., grayscale, RGB, or indexed-color), and user-defined color spaces. An extension to the TIFF called GeoTIFF allows the TIFF image to

<sup>3</sup> Figure 4 and Figure 5 were created by Dr. Reid Priedhorsky for his review on the print quality of topographic maps, which can be found on <http://reidster.net/trips/maps/>

store georeferencing information. In contrast to the fact that the TIFF stores only raster data, a format that stores both raster and vector data is the PDF (Portable Document Format). In addition, the GeoPDF built on the PDF is a container that has been specifically designed to host geospatial data. It can store multiple layers of raster and vector data and their georeferencing information. For example, the digital USGS topographic maps are now distributed in GeoPDF format with a number of data layers, including orthoimagery, transportation, geographic names, and contour lines.

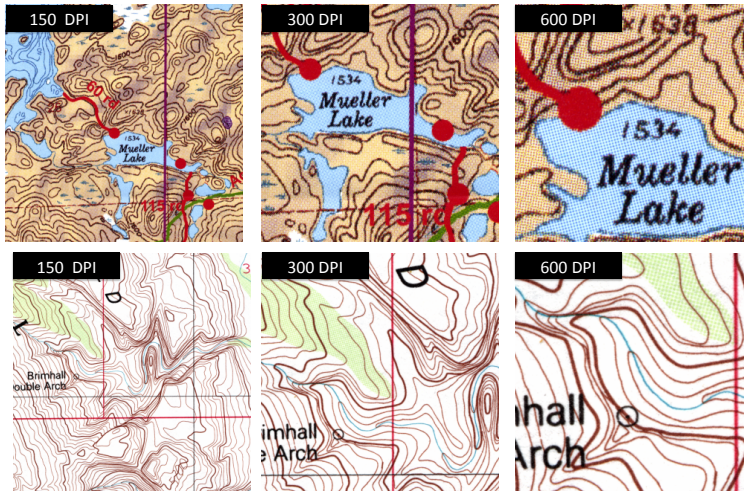


Figure 4 Maps scanned at various resolutions but with the same image dimension where lower DPI values allow the image to cover a larger area (but fewer image details) than greater DPI values

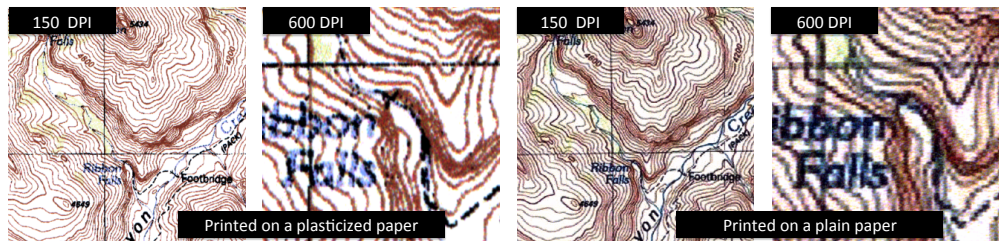


Figure 5 Two scans of the same map extents (at 150 and 600 DPI, respectively) printed on two different materials

### 3.1 Color Image Segmentation (CIS)

In map processing, similar to most other image analysis and pattern recognition tasks, image segmentation represents a crucial pre-processing step whose outcome directly influences subsequent processing steps (Fu and Mui, 1981; Pal and Pal, 1993). The basic intention of image segmentation is to divide an image into exclusive regions such that each region is homogeneous, but the union of any two neighboring regions is not (Cheng and Sun, 2000).

Most map images contain color (i.e., are encoded in a color space such as RGB, HSI or CIE  $L^*u^*v$ ) not just grey values. In such cases color image segmentation (CIS) can be applied in this pre-processing step (Cheng et al., 2001; Lucchese and Mitra, 2001). Most maps contain thematic layers represented in predefined colors (e.g., blue for hydrography, red for elevation, or green for vegetation), and different color spaces have been utilized in the past to perform CIS. The main goal is hence identifying color-homogeneous regions and reducing the number of color values found in the original map images to the number of existing map color layers. This allows for characterizing CIS in color maps as a typical classification problem based on color and spatial attributes (Cheng et al., 2001), which means that resulting homogeneous regions must show spatial contiguity and that connectivity has to be preserved.

Numerous existing approaches for CIS have been tested separately or in combination in map processing efforts and the basic techniques are briefly explained below. More detailed overviews of these techniques can be found in Cheng et al. (2001) or Lucchese and Mitra (2001).

*Histogram thresholding* is an attribute-space based technique that uses histograms of color values found in an image to identify values or value ranges that occur frequently and thus could represent possible color classes (Sahoo et al., 1988; Pal and Pal, 1993; Cheng et al., 2001). This approach searches for global and local maxima in frequency distributions of color values and assumes that peaks in a histogram correspond to color classes thought to be occurring spatially adjacent. Spatial contiguity is not explicitly accounted for in histogram thresholding. Histograms are usually created separately for each color space dimension and results are combined in different ways. If the underlying image is a grayscale image, the histogram-based approach uses only one frequency distribution. Figure 6 shows an example of grayscale histogram thresholding. The original map (left) is first converted to a grayscale image (middle). Then the grayscale histogram (bottom) of the grayscale image is used to determine the grayscale range of the background pixels for separating the map features from the map background. The bi-level image (right) is the thresholding result when the pixels that have grayscale values between 199 and 255 (which is the map background corresponding to the blue portion toward the right in the histogram) are removed. Homogram-based approaches derive from histogram-based thresholding and attempt to overcome the lack in contiguity by implementing homogeneity criteria and applying histogram-based thresholding using locally homogeneous pixel locations (Cheng et al., 1998 and 2002).

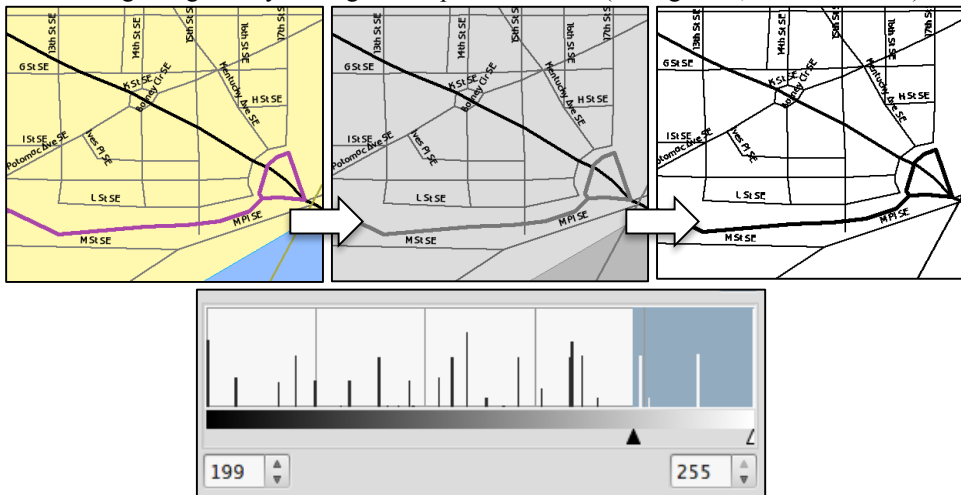
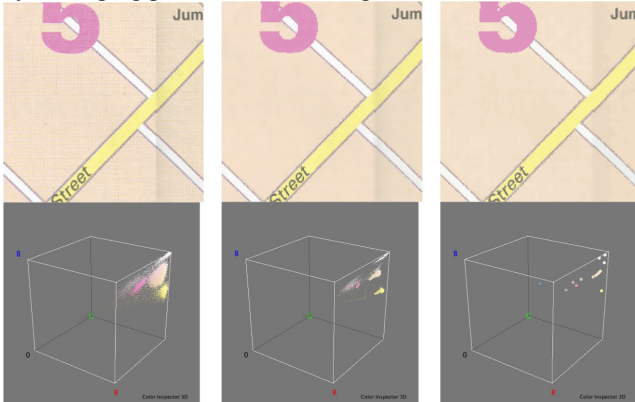


Figure 6 An example of grayscale thresholding

*Color space clustering* is an unsupervised classification approach to identify classes of objects without any prior knowledge (Bow, 1992); it can be seen as the multi-dimensional extension of thresholding methods (Fu and Mui, 1981). Clustering makes use of all dimensions of the selected color space and attempts to identify statistically significant clusters in this color space assuming that high frequencies of similar color value combinations potentially describe main color classes (Figure 7). Existing algorithms that have been frequently applied and adjusted in different ways in the context of map processing are K-means (or C-means) (McQueen, 1967), the fuzzy set based alternative, fuzzy C-means (applied to CIS in e.g., Wu et al. (1994) and Zheng et al. (2003)), or ISODATA (Iterative Self-Organizing Data Analysis) (Ball and Hall, 1965). The basic idea of these algorithms is that  $n$  observations are partitioned in  $k$  clusters in that each observation belongs to exactly one cluster (K-means) or to different clusters at varying degrees (fuzzy C-means). The decision as to which class each observation is assigned depends on distance measures (e.g., the Euclidean distance) in a color space between a cluster center and the observation. Similar to the thresholding approach, spatial contiguity of color values is not explicitly accounted for without consideration of homogeneity in a local plane. Also the number of clusters in the underlying image has to be specified, potentially introducing subjectivity into the process. To overcome this limitation non-parametric clustering methods, such as the Mean-Shift algorithm (Comaniciu and Meer, 2002), can be used in color segmentation without prior knowledge of the number of resulting clusters (i.e., the number of colors in the quantized image). Figure 7(b) shows the color image segmentation results of the Mean-Shift algorithm, which merges similar colors if they are spatially close in the image plane (Chiang and Knoblock, 2013).



*Region-based approaches* are based on the principle of grouping pixels into homogeneous groups applying techniques such as region growing, region splitting, or region merging. These techniques are often called and classified as image-domain based techniques (Lucchese and Mitra, 2001) because they take spatial contiguity (or compactness) of homogeneous regions as well as connectivity between these regions directly into account. Region growing approaches typically start with the definition and placement of so-called seeds – pixels that have to fulfill predefined criteria of color types and local homogeneity (Rosenfeld and Kak, 1982). These seeds are the starting positions for testing their surrounding pixels for similarity to the seed color values and for homogeneity. If the surrounding pixels fulfill the predefined conditions, they are added to the region. In this way regions (i.e., groups of similar color occurrences) around these seeds are built (grown) sequentially until the image is partitioned into homogeneous groups (Figure 8) followed by a merging process for small regions to maximize the level of overall homogeneity.



(a) An example tile (b) Mean-shift results (c) K-means results (K=16)

Figure 7 The principle of color space clustering: each pixel is assigned to one of the classes based on distances between its corresponding position and different cluster centers in color space; the resulting images (top) appear similar even though the numbers of colors in the color space (bottom) are significantly reduced after applying each clustering algorithm.

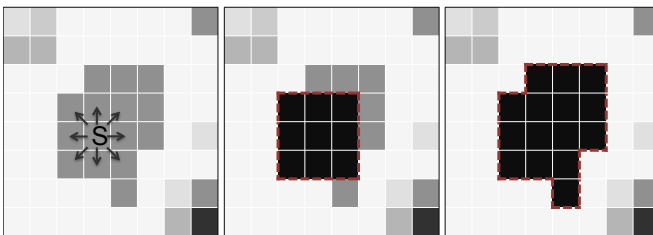


Figure 8 The principle of region growing is to identify a seed pixel for a region of interest and search the local environment for similar pixel values and, if homogeneity criteria are fulfilled within this local environment, the region is grown; this step is then repeated until no further pixels can be added.

Split-and-merge techniques start with the partitioning of the image into regions and then examining these regions for homogeneity. If the regions are found to be non-homogeneous they are further partitioned (split) until homogeneous sub-regions are found – similar to quad-tree data representations (Bow, 1992; Jain et al., 1995) (Figure 9).

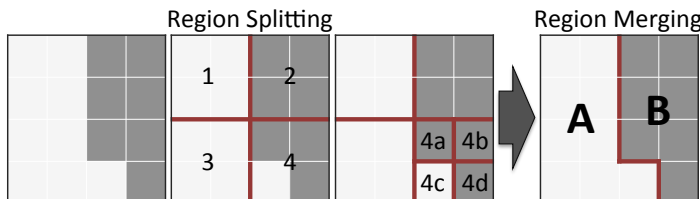


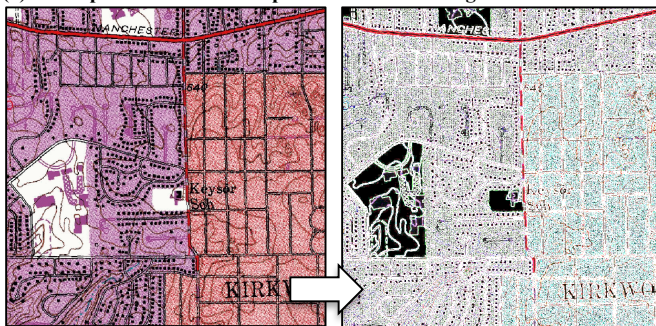
Figure 9 The principle of merge-and-split approaches. Region splitting searches for homogeneous regions in an image by hierarchically partitioning the area into quadrants (as in the quadtree approach). This partitioning process continues until there are no heterogeneous regions left. Region merging merges adjacent sub-regions if the homogeneity criterion can still be warranted.

After this splitting phase small regions are merged under the constraint of maintaining homogeneity criteria. Region-based approaches are more robust against noise especially where contiguity and connectivity criteria are important for image processing but they are computationally more expensive. Also, region-growing results depend on the location of seeds or seed regions as well as on the order and direction of pixel examination. To overcome some of these limitations region-based approaches are often combined with color-space-based approaches such as clustering or histogram-based techniques in a preliminary step to identify a number of seed candidates.

Edge detection techniques work on the principle of detecting contrasts in color values between regions and thus identifying discontinuities, i.e., abrupt changes in color values using local filtering operators (Fu and Mui, 1981; Pal and Pal, 1993). Complete segmentation results can only be achieved in concert with other techniques such as region-based approaches. Traditionally edge detection has been performed in grayscale images and can be classified in parallel and sequential techniques (Pal and Pal, 1993). Parallel means that the decision of one location to be part of an edge is independent of the decisions made for other pixels and thus differential operators to detect edges can be applied simultaneously anywhere in the image. In sequential techniques for edge detection, the decision whether or not a pixel is part of an edge is dependent on pixels examined previously and thus the process is highly dependent on the starting point. Edge detection in color images is based on the same approaches described above for monochromatic (or grayscale) images but makes use of the richer color information. Principally, discontinuities in color space including all color channels are detected by calculating gradients in single color channels as in grayscale images, and the results are then combined in different ways. In order to increase robustness of the process some uniformity constraints of detected edges are added. Edge detection techniques show limitations in images with poor contrasts or disconnected features as well as when noise is present due to the small spatial extent of the local differential operators. Figure 10 shows edge detection results from a TIGER/Line map and a USGS topographic map. The results from the topographic map are quite noisy due to the poor graphical quality of the scanned image.



(a) A sample TIGER/Line map and the detected edges



(b) A sample USGS topographic map (the purple areas represent the updated features since the original survey, and the white areas represent the areas with scant or no vegetation) and the detected edges

Figure 10 Edge-based image segmentation attempts to calculate gradient functions in order to find discontinuities that define edges between regions in the image (black pixels in the images to the right represent zero gradient as a result from the local gradient function)

Finally, artificial neural networks (ANN) have a long history of being implemented to solve classification and clustering problems in pattern recognition tasks including CIS in map images. In short, neural networks consist of numerous computational elements, which are called processors,

connected by links with variable weights (Bow, 1992). Such a neural network allows for representing highly complex sets of interdependencies that can be of particular advantage in CIS if the image suffers from blurring or mixed pixels making class assignment a more complex task. One example is the Hopfield network (Bow, 1992) whose network architecture is derived from the energy function and applied to CIS in e.g., Campadelli et al. (1997). Here image segmentation is considered as the problem of minimizing a suitable energy function. Several other neural-network-based CIS approaches exist such as self-organizing maps (SOM), back propagation (BP), or Learning Vector Quantization (LVQ), but have not been applied to map processing tasks. Typical problems of neural-network-based approaches to image segmentation are the extended training time and high specificity to the image of interest (lack of generality).

Color image segmentation, not only in map processing tasks, is frequently carried out by making use of different combinations of above described segmentation techniques (den Hartog et al., 1996; Centeno, 1998; Santos et al., 1998; Cordeiro and Pina, 2006; Leyk and Boesch, 2010; Leyk, 2010). However, if maps suffer from low graphical quality and excessive complexity, color image segmentation represents a difficult process in which preservation of connectivity and shapes of map objects is particularly crucial. Relevant approaches that aim at overcoming such problems in map images will be reviewed in more detail in Section 4.1.

### 3.2 Geographic Feature Extraction and Recognition

The process of extracting and recognizing geographic features from scanned maps utilizes and combines a variety of techniques that stem from the fields of document analysis and image processing and fall into three major categories: template matching, morphological operators, and shape descriptors.

*Template matching techniques* are widely used in computer vision, pattern recognition, and document analysis research. A detailed survey of various template matching algorithms and their applications can be found in Brunelli (2009). In general, the main goal of these template-matching algorithms is to find objects in the document of interest that are similar in shape and size to an object given as a template. The most commonly used algorithm in map processing is correlation-based template-matching (Rosenfeld and VanderBrug, 1977), which evaluates the correlation between the pixel values of a template and the pixel values of the target image within a window of the same size as the template to find the objects of interest. Here we briefly introduce the principles of correlation-based template matching exemplified on a road intersection detector recently used in map processing work (Chen et al., 2008; Chiang et al., 2009).

Given a road intersection template,  $T$ , of the size  $w$  by  $h$  pixels as shown in Figure 11(a), the road intersection detector searches the input map shown in Figure 11 (b) within a moving (or sliding) window,  $S$ , of the size  $w$  by  $h$  pixels. The matching algorithm generates a similarity value correlating the contents of the map document within the moving window with the contents of the template. For example, a normalized cross correlation can be computed (Chen et al, 2008) as:

$$\text{Normalized Cross Correlation } (T_{x,y}, S_{X,Y}) = \frac{\sum_{y=1}^h \sum_{x=1}^w T(x,y)S(X+x,Y+y)}{\sqrt{\sum_{y=1}^h \sum_{x=1}^w T(x,y)^2 \sum_{y=1}^h \sum_{x=1}^w S(X+x,Y+y)^2}}$$

where  $T(x,y)$  equals one, if the pixel at position  $(x,y)$  in the template is a foreground pixel (i.e., is part of the road intersection template); otherwise  $T(x,y)$  equals zero.  $S(X+x,Y+y)$  equals one, if the map pixel at  $(x,y)$  in the moving window matches the color of the pixel at  $(x,y)$  in the template; otherwise  $S(X+x,Y+y)$  equals zero. The location  $(X,Y)$  is the current window shift position. Each matching interaction shifts the window position by one pixel in either the horizontal or vertical direction (overlapping the last window). The normalized cross correlation measure can range from 0 to 1 where 0 means the map contents within the moving window are completely different from the template and 1 means a perfect match. By adjusting a threshold on the correlation measure, we can identify map objects that are geometrically similar to the template (i.e., a high threshold is used to identify map objects that match most of the template). Figure 11(c) shows an example of the road intersections (red intersections in the green areas) that can be identified using the described template-matching algorithm based on a correlation threshold.

There are more sophisticated template matching algorithms that detect objects with a similar shape but different sizes (scale-invariant) or in different orientations (rotation-invariant). Rotation-invariant template matching algorithms often use shape descriptors (explained at the end of this section) instead of using every pixel in a moving window to compute the similarity values and are more computationally intensive. Figure 11(d) shows the detected road intersections (red intersections in the green areas) when a rotation-invariant template matching algorithm is used.

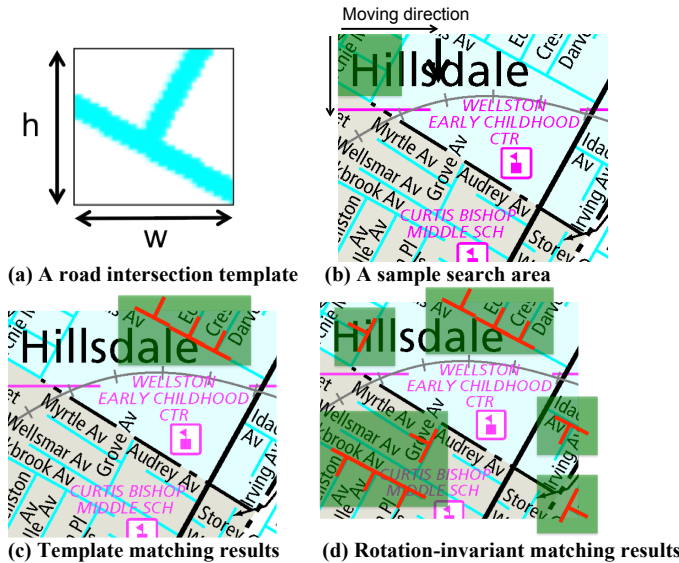


Figure 11 Using template matching to identify a specific type of road intersections

*Morphological operators* are commonly used to modify image contents to facilitate and improve the extraction and recognition of point, linear, and area features. In more complex settings morphological operators have been applied for identifying parallel linear features (Yamada et al., 1993; Chiang et al., 2009), reconnecting broken linear features (Chiang and Knoblock, 2013), separating linear features from text (Luo and Kasturi, 1998), removing noise objects for recovering large area features (Angulo and Serra, 2003), and converting areas of pixels to vector format (Doermann, 1998; Tombre et al., 2000). Basic morphological operators are binary operators that deal with images with two colors, i.e., bi-level images, and can be extended to process grayscale and color images. These traditional morphological operators are based on the hit-or-miss transform using masks of various sizes and shapes (see Pratt (2001) for a detailed description of common morphological operators). A hit-or-miss transform scans every pixel and its local environment (e.g., a square mask with 3x3 pixels) in an input bi-level image. A “hit” condition arises if the mask matches a pixel and the pixel’s neighborhood pattern, i.e., the local morphological conditions of interest; otherwise, it is a “miss” condition. Each morphological operator employs a different mask to perform the hit-or-miss transform and triggers specific actions in response to a “hit” or “miss” condition. This hit-or-miss transform is a type of template matching algorithm that generates binary results (either a hit or a miss) instead of similarity measures (in the range [0, 1]) as described above in the road intersection detection example.

The most commonly used morphological operators also in map processing tasks are binary operators (in contrast to the multi-level morphological operators that apply to grayscale or color images) because the results of color image segmentation can be conceptualized as a set of bi-level images representing individual map layers (Agam and Dinstein, 1996). Binary morphological operators that are often employed in combination include the dilation, erosion, closing, opening, and thinning (skeletonizing) operators. The aim of a dilation operation is to expand the region of foreground pixels if the hit condition is fulfilled. In map processing, a dilation operator is commonly applied to fill gaps of broken lines or holes in presumably homogenous areas. For example, if a background pixel is found with one or more foreground pixels within its 3x3 pixel neighborhood (i.e., a “hit”), a binary dilation operator with a 3x3 square mask converts the background pixel to a foreground pixel (i.e., the action in response to a “hit”) thus expanding the

area of foreground pixels. Figure 12 shows an example of applying a binary dilation operator iteratively to merge road edges.

The idea of a binary erosion operator is to reduce the region of foreground pixels. For a foreground pixel with one or more background pixels within the 3x3 pixel neighborhood (i.e., a “hit”), a binary erosion operator with a 3x3 square mask converts the foreground pixel to a background pixel (i.e., the action in response to a “hit”) thus reducing the area of foreground pixels. Figure 12 shows an example of applying an erosion operator iteratively to reduce road areas.

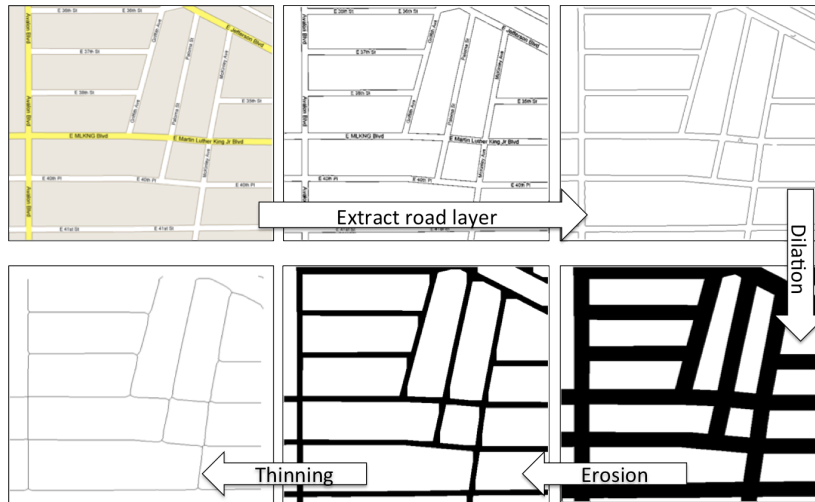


Figure 12 Using binary morphological operators to extract road centerlines (Chiang et al., 2009)

The closing operator is a dilation operator followed by an erosion operator, and the opening operator is an erosion operator followed by a dilation operator. The closing operator is used to remove holes and smooth region boundaries without expanding region areas. For example, if a closing operator with a 3x3 square mask is applied, the background areas that are smaller than 3x3 will be first conveyed to the foreground by the binary dilation operator and the foreground area will grow in all directions. Next, the erosion operator will shrink the foreground area in all directions to offset the expansion of the foreground area from the dilation operator. In contrast, if an opening operator with a 3x3 square mask is applied, the foreground objects that are smaller than 3x3 will be first converted to background pixels and the foreground area will shrink in all directions. Next, the binary dilation operator will expand the foreground area in all directions to offset the shrinking of the foreground area from the binary erosion operator.

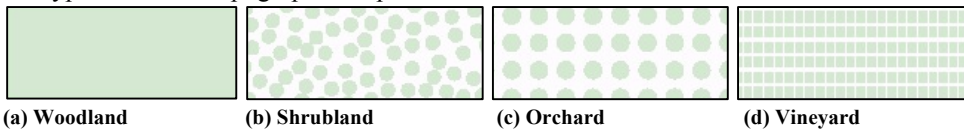
Due to its simplicity, the thinning operator is widely used in raster-to-vector conversion to produce a so-called skeleton of a group of foreground pixels (see Hori and Okazaki (1992), Rössli and Monagan (1995), and Janssen and Vospepoel (1997) for more sophisticated, high quality vectorization techniques). The thinning operator is a conditional erosion operator with an additional verification step. The first step of the thinning operator is to label every foreground pixel that connects to one or more background pixels (i.e., the same idea as the binary erosion operator) as a candidate pixel that may be converted to a background pixel. Next, in the verification step each candidate pixel is examined to determine if the conversion of that pixel causes any disruption of original line branches or crossings. This verification ensures that the original structure of the considered object is not compromised. One common critique of the thinning operator is that the resulting skeletons do not accurately represent the original shape of the object in terms of geometry and topology (Tombre et al., 2000). Hence, the results of the thinning operator often require manual editing or subsequent shape adjustment to correct the thinning results. Figure 12 shows an example of applying a generic thinning operator to identify the road centerlines.

*Shape descriptors* have commonly been used to identify text and symbolic features in map processing. Shape descriptors range from simple metrics of height, width, area, compactness or the bounding box of a connected component to computationally more complex ones, such as descriptors based on the discrete Fourier transform for estimating texture representations (Adam et

al., 2000; Chiang and Knoblock, 2006) or the Hough transform for identifying imperfect linear objects (e.g., broken lines) (Kasturi and Alemany, 1988; Chen and Wang, 1997; Dhar and Chanda, 2006; Chiang and Knoblock, 2013).

Simple shape descriptors (e.g., geometric measures of height, width, or area) usually rely on a connected component analysis. First connected components, i.e., regions or groups of pixels that are defined by certain connectivity and adjacency criteria, are identified and labeled in the input image. Adjacency (and thus connectivity) can be conditional on the existence of pixels next to the pixel of interest either only in horizontal or vertical directions (von Neumann or “diamond-shaped” neighborhood) or in both, horizontal/vertical and diagonal directions (Moore or “square-shaped” neighborhood). Every pair of foreground pixels that fulfills the underlying adjacency condition belongs to the same connected component. Next, sets of attributes – shape descriptors – of the individual connected components are calculated; these are subsequently used to identify specific features such as text objects or various symbols (see Salmon et al. (2007) for a detailed description of common shape descriptors). For example, given a scanned map that contains text labels and road lines, various descriptors (or attributes) such as width, height, and compactness of the text characters can be empirically determined in the map and subsequently used to filter out road lines and retain character-like objects (or connected components) for recognition (Li et al., 2000; Cao and Tan, 2002).

Shape descriptors based on the discrete Fourier transform (Brigham, 1988) have played an important role in multiple texture classification applications due to their ability to generate distinct attributes for different texture representations (Randen and Husoy, 1999). The discrete Fourier-transform maps an image into the frequency domain where the strength of each frequency is represented by one of the estimated Fourier coefficients. Since the texture representations of the same map features are usually similar within a local environment (but vary across different map features), the Fourier transform (or the Fourier-related transform, such as the discrete cosine transform (DCT)) can be used to distinguish between map features (Chiang and Knoblock, 2006). For example, Figure 13 shows four green patterns that are used to depict different vegetation/land use types in USGS topographic maps.



**Figure 13 Textures used to represent different vegetation/land use types in USGS topographic maps<sup>4</sup>**

Another technique that is extensively used in map processing is the Hough transform. The Hough transform is a technique frequently used to identify imperfect lines (e.g., broken lines or dashed lines) (Duda and Hart, 1972). For example, Figure 14(a) shows two lines in a noisy image (white pixels are background); parts of the line pixels are missing. To detect the two lines in Figure 14(a), the Hough transform first transforms the image to the Hough space (Figure 14(b)) (black pixels are the background). In the Hough space, a sinusoidal curve represents a set of straight lines that pass through a point in the image plane. A point in the Hough space represents a straight line in the image plane, which is described by two parameters:  $r$  and  $\theta$ . As shown in Figure 15, in the image plane, the parameter  $r$  is the distance between the straight line and the point of origin, and  $\theta$  is the angle of the shortest line between the point of origin and the straight line. Using the two parameters,  $r$  and  $\theta$ , a straight line of certain orientation is described as:

$$r = x \cos \theta + y \sin \theta$$

For the set of straight lines that pass through a point,  $P(x_p, y_p)$ , in the image plane, the sinusoidal curve in the Hough space is:

$$r(\theta) = x_p \cos \theta + y_p \sin \theta$$

<sup>4</sup> Credit: U.S. Geological Survey (USGS topographic map symbols)

When two sinusoidal curves generated from two points  $P(x_p, y_p)$  and  $Q(x_q, y_q)$ , intersect in the Hough space, the intersection point represents a straight line in the image plane that passes through two points  $P(x_p, y_p)$  and  $Q(x_q, y_q)$ . Hence, by finding the local maxima in the Hough space where many of the sinusoidal curves intersect, we can detect possible straight lines in the image plane even if the lines are constituted from imperfect objects. Figure 14(c) shows the detected straight lines in the image plane. Since identifying the local maxima in the Hough space requires only a simple grayscale thresholding in the Hough space, the Hough transform is a robust and straightforward choice in map processing for detecting linear features such as road lines (Yamada et al., 1993; Dhar and Chanda, 2006) or for identifying straight map labels (Chen and Wang, 1997; Chiang and Knoblock, 2013).

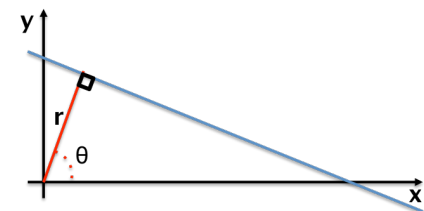
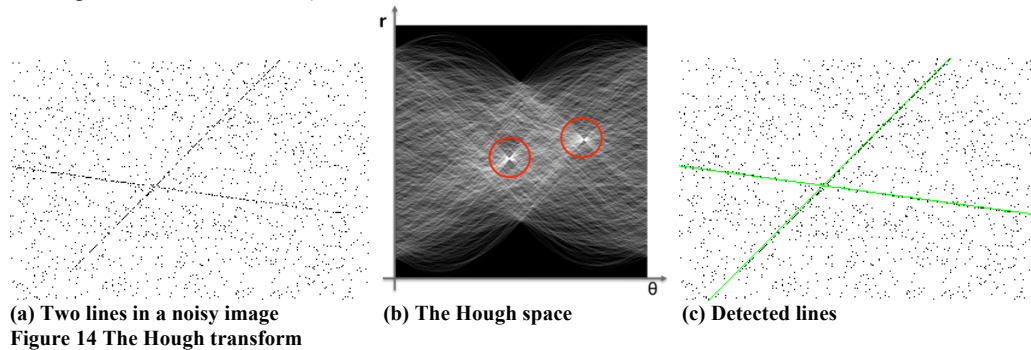


Figure 15 Using  $r$  and  $\theta$  to represent a straight line

#### 4. A REVIEW OF MAP PROCESSING EFFORTS FOR THE EXTRACTION AND RECOGNITION OF CARTOGRAPHIC INFORMATION

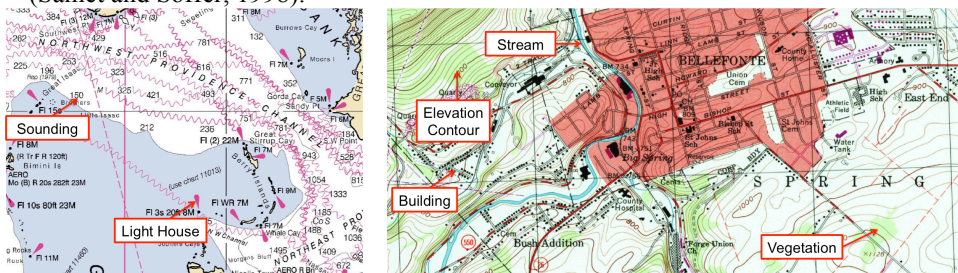
Earlier approaches to map processing pursued different objectives. Some systems were designed as general recognition systems to extract multiple features from a map document (Wigand, 1988; Ebi et al., 1994; Frischknecht et al., 1998; Bessaid et al., 2003; Dhar and Chanda, 2006) while others are highly specialized approaches recognizing one well-defined set of features in the map (Fayek and Wong, 1996; Watanabe and Zhang, 1997; Miyoshi et al., 2004; San et al., 2004; Xin et al., 2006). Typically, various preprocessing steps have to be conducted such as image cleaning and filtering followed by separating the feature of interest from other overlapping map symbols (e.g., Gamba and Mecocci, 1999; Cao and Tan, 2002; Bajcsy, 2003; Leyk and Boesch, 2009), which increases the complexity of the recognition process. This complexity can be seen as one reason for the lack of automation in many recognition tasks.

We describe the recent approaches to map processing organized by the geometric properties of the features of interest (i.e., line or area features). Here first we describe how the various thematic or map layers (geographic features) are represented (Figure 16):

- Road features are commonly represented as line features – single (road centerlines) or parallel (road edges) – or as area features (e.g., Maderlechner and Mayer, 1995; Bin and Cheong, 1998; Itonaga et al., 2003; Chen et al., 2004; Dhar and Chanda, 2006; Bucha et al., 2007; Chiang et al., 2012; Chiang and Knoblock, 2013). Road intersections are often extracted and represented as point features since they provide distinct characteristics in road networks (e.g., Habib et al., 1999; Liu, 2002; Chiang et al., 2009; Henderson and Linton, 2009).
- Vegetation features often are represented by simple background filling areas but can also appear in the form of vegetation symbols (Ebi et al., 1994; Frischknecht et al., 1998) or symbol

compositions with or without linear features as boundaries (Dhar and Chanda, 2006; Leyk et al., 2006; Leyk and Boesch, 2009).

- Text or text labels are mostly part of the black layer and appear in different styles, font sizes, orientations and can even appear curved; recognition approaches have to deal with these difficulties (e.g., Yamada et al., 1993; Deseilligny et al., 1995; Chen and Wang, 1997; Chen et al., 1999; Gllavata et al., 2004; Dhar and Chanda, 2006; Pezeshk and Tutwiler, 2008, 2010a, 2010b, 2011). In addition text objects are often overlapping with other features in the map (e.g., Kasturi and Alemany, 1988; Luo and Kasturi, 1998; Yin and Huang, 2001; Cao and Tan, 2002; Chiang and Knoblock, 2011).
- Hydrographical map features (in most cases the blue layer) include streams that are commonly represented as linear or area features depending on the map scale (Ebi et al., 1994; Angulo and Serra, 2003; Dhar and Chanda, 2006; Henderson et al., 2009) or wetland areas often shown as a spatial distribution of single or clustered symbols (Leyk and Boesch, 2010).
- Building symbols are in most cases small rectangular area features or can be elongated shapes (in urban areas with higher building densities); typically they are part of the black map layer (e.g., Fayek and Wong, 1996; Frischknecht and Kanani, 1998; Liu, 2002; Angulo and Serra, 2003). Building symbols often overlap with other map features such as roads or text.
- Elevation contours are linear features that belong in most cases to the red or brown map layer and follow certain geometric properties, i.e., they must not intersect each other (e.g., Yamamoto et al., 1993; Khotanzad and Zink, 1996 and 2003; Dupont et al., 1998; Salvatore and Guittion, 2004; San et al., 2004; Chen et al., 2006; Pezeshk and Tutwiler, 2008; Samet and Hancer, 2012; Miao et al., 2013).
- Other cartographic symbols that are of possible interest in map processing include features from nautical charts (Trier et al., 1997), symbols for landmarks, political boundaries (Gamba and Mecocci, 1999) or churches (Frischknecht and Kanani, 1998), and other legend-based symbols (Samet and Soffer, 1998).



**Figure 16** Various thematic layers found in maps for possible extraction: a nautical chart (National Oceanic and Atmospheric Administration (NOAA)) (left) and a topographic map (USGS) (right)

The following subsections describe and review map-processing efforts in more detail focusing on the most relevant studies found in the literature, sorted by steps typically done in map processing: separating raster layers (segmentation), extracting area features, extracting composite features and other map symbols, line detection, text recognition, interactive map processing, and map registration. In numerous studies the reader can find accuracy measures for proposed map processing techniques such as percent correctly classified, recall, precision, or the kappa coefficient of agreement. However, objective measures are difficult to compute due to the lack of sufficient (“complete”) reference data and inherent subjectivity, i.e., it is always difficult to claim that the extraction of a cartographic symbol is perfect or acceptable.

#### 4.1 Separation of Raster Layers (Segmentation)

Section 3.1 described the most commonly used general techniques for color image segmentation applied to map processing tasks, which has the main goal of separating the different color layers found in a map in order to improve the performance of subsequent processing steps. This section reviews specialized image segmentation approaches developed for more complex and graphically inferior map images (Figure 17), which pose particular challenges. Numerous map-processing studies are designed specifically for noise removal (Mello et al., 2012) conducted on well-



conditioned maps and segmentation often represents a single preprocessing step based on histogram thresholding or color space clustering. These approaches are excluded here. In this section existing CIS approaches are grouped into three different categories according to the information domain they use (color space and image plane): (i) approaches that use only color space, (ii) approaches that use color space and the local context in the image plane implicitly, and (iii) approaches that use color space and local spatial relations in the image plane explicitly.

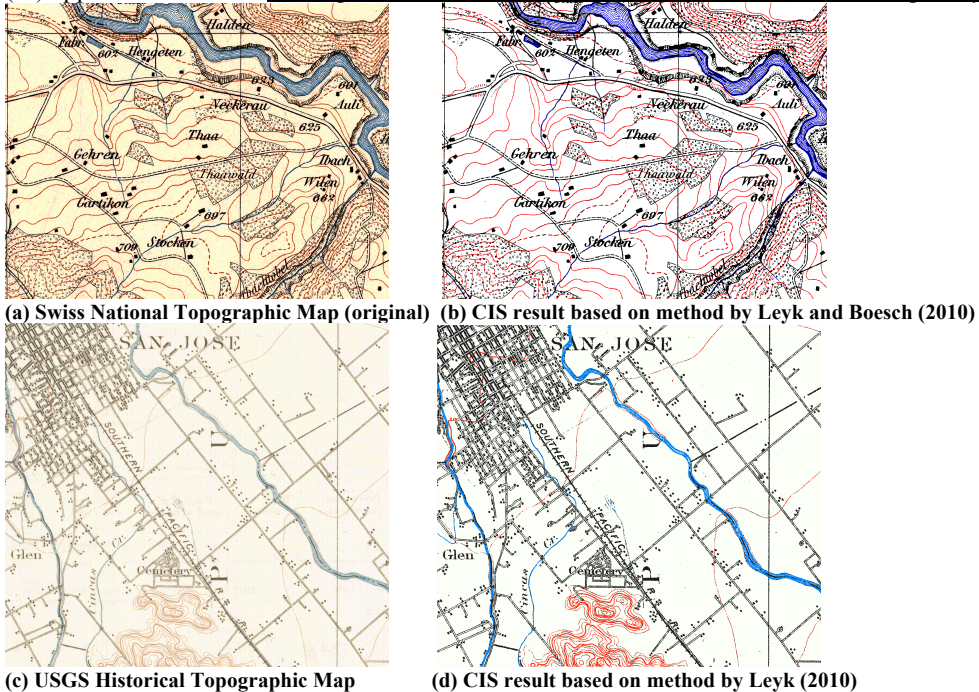


Figure 17 Two exemplary CIS results from historical topographic maps. The results in (b) and (d) are shown in pure colors in quantized images, blue for hydrography, red for contours, black for the black layer, as well as white for background.<sup>5</sup>

Some recent CIS techniques in maps are solely based on color space. For example, in a study on Indian survey maps image enhancement is applied in a first pre-processing step to change each pixel value to one of the possible RGB color space extremes such as  $\{255,0,0\}$  or  $\{0,0,255\}$  representing initial clusters in color space (Dhar and Chanda, 2006). Next, the K-means algorithm is applied to allocate each original pixel in the map to one of the initial clusters based on minimum distance in color space. The RGB values of the cluster centers are then calculated based on normalized feature vectors of all the pixels that have been allocated to the corresponding initial color cluster. In a final separation step, each pixel is allocated to the nearest final (adjusted) prototype and for each feature layer one bi-level image is generated. The approach contributes to high recognition rates in subsequent map recognition stages, but assumes high levels of homogeneity within feature layers and well-defined color values.

Another CIS approach that works entirely in color space aims at the separation of color objects in topographic maps. Based on tonal values, Cordeiro and Pina (2006) define different cut levels for the identification of color objects in RGB color space. For each color layer, sampled color values define cut-level values for sections within the color space cube. These sections are then either intersected in color space to define noise “regions” (background) or they are unified to create so called “co-regions” in color space that define the color objects of the different colored map layers. The process of isolating the color objects is performed layer-wise after already isolated layers were eliminated from the scanned image. This approach seems to work on maps with clearly defined color values, but needs to be tested on maps with higher variability in color values and on maps with false colors. Also, defining the cut-levels introduces some subjectivity.

<sup>5</sup> Reproduced by permission of swisstopo (BA13123)

Some approaches to color image segmentation in maps make *implicit use of the local spatial context in the image plane in addition to information from the color space*. One example refers to a segmentation process in utility maps. The process starts with a sharpening step to un-blur the image using Laplacian linear filters (den Hartog et al., 1996). Next a global grey value thresholding step with *hysteresis* is done. This means they first define a grey value range, and identify pixels with values above and below this range as definite background and object pixels, respectively. In a second step the pixels between the two thresholds are classified as object pixels only if they are directly connected to an already classified object pixel (adjacency in the image plane). This global segmentation is input to a complex recognition process. If inconsistencies can be detected in the recognition result, a re-segmentation (or top-down segmentation) is performed to correct the errors made in the global segmentation. While integrating prior knowledge improves the segmentation and subsequent recognition, den Hartog et al. (1996) describe a highly laborious and complex technique that requires intensive user intervention and is specific to grayscale utility maps.

A second example is a study that uses hue-histograms (from the HSV color space) to define thresholds of feature layers in different sub-regions of a scanned topographic map image (San et al., 2004). This approach is able to adjust for varying cut-off values to identify map layers by evaluating bi-modal sub-regional histogram distributions. In order to remove isolated small regions (noise) they perform an edge-preserving smoothing technique. Their approach incorporates an innovative step in partitioning the image to adjust for color variability, but has not been tested on different maps.

A third study that belongs to this category is based on Eigenvector Line-Fitting in RGB color space to segment USGS topographic maps. In this work Khotanzad and Zink (1996) propose a segmentation technique that overcomes problems of scanner-related false coloring and aliasing. They use a local window (7x7 pixels in the image plane) to classify transitional pixels between objects and background. Their approach is later applied and adjusted by Chen et al. (2006) who developed a technique called "local window segmentation." This method applies a line-tracing algorithm to repair gaps and thick (i.e., merged) contour lines locally to improve the overall segmentation result. This approach showed acceptable results on well-conditioned (or more recent) USGS topographic maps but has never been tested on other maps.

The third category of CIS approaches includes techniques that use *color space information for initial color prototype definition and make explicit use of spatial relations* to perform the image segmentation. For example, in a histogram-based approach on German topographic maps, color cluster centers are detected in the histogram of the  $u'v'$  chromaticity plane ( $L^*u^*v^*$  color space). They apply a peak detection technique adjusted to this two-dimensional cumulative frequency distribution (Ebi et al., 1994). These cluster centers are then used to perform the segmentation of map layers using chromaticity and lightness criteria. Finally, they employ region growing based on containment tests and structural texture analysis to fill unclassified areas in the map. While this approach has been demonstrated for maps with rather well-defined color layers, the use of spatially explicit relations in the region growing step provides greater flexibility to process maps with lower graphical quality.

Other work that can be grouped in this third category combines color space, frequency domain, and the image plane to improve color image segmentation in low-quality Swiss historical topographic maps. In this approach only locally homogeneous pixels are included in the frequency distribution of the map image (Leyk and Boesch, 2010). The most frequent values (peak) and similar values (similarity is defined by distance in color space) are assigned to the first color layer and removed from the frequency distribution. The same process is performed to identify the remaining (initially hidden) color prototypes. These prototypes are then input to a seeded region growing process to identify connected regions based on color similarity and spatial adjacency in the local image plane. The method (Figure 17(a) & (b)) produces acceptable results but requires user-specified parameters; it also suffers from excessive processing time. This approach provided the basis for a two-stage CIS approach in historical USGS topographic maps (Leyk, 2010) to overcome color variability found in features of the same map layer. In the first step a sample of pixel values is collected from the image to determine global color prototypes, initially based on the distance in color space to the color extremes representing the map layers (e.g., {255,0,0} in RGB for red). The prototype positions in color space are adjusted sequentially with each pixel

value added until stabilized. The prototypes are then used to define homogeneous core regions of map layers. In the second step the color prototypes are re-computed based on a second sample drawn from the edges of homogeneous regions to account for color variability in map layers at transitions to background thus improving the subsequent spatial expansion of regions (Figure 17(c) & (d)). This approach shows good results and shorter processing time on low graphical quality maps but still needs to be tested on other maps.

Summarizing the above efforts, current challenges that can be identified for CIS in scanned maps are preserving the spatial context of segmentation results, ensuring the connectivity of homogeneous map elements, and maintaining the shapes of map objects while accounting for color variability of map contents within one map page and across maps. This variability is caused by finite-size sampling spots, which results in blurring of color boundaries and mixed-color pixels. Thus, even high quality paper maps with uniformly colored features will yield scanned images with considerable variation in color. All these aspects are crucial for generating topologically correct cartographic information for input into a GIS. Furthermore, more generic CIS approaches that would make it possible to process different maps or types of maps are in urgent demand. Such tests are rarely (if at all) done. In general it can be stated that the complexity of CIS efforts increases with decreasing quality of the map image, which often relates to the age of the scanned map document. Accordingly, the degree of automation is lower if the methodological steps become more complex and the solution is often highly map or map series-specific. However, the most promising strategy seems to be the combination of color space and image plane properties to produce robust segmentation results. As stated initially, segmentation techniques are sometimes difficult to differentiate from extraction and classification steps, which impedes tracking the most recent developments.

#### 4.2 Extraction and Recognition of Singular Map Features

Symbols can be described as sets of distributed graphic signs or shapes to represent some feature or property of the world. Symbol recognition uses knowledge of the semantics attributed to these symbols and applies rules to extract them. Numerous attributes and techniques can be used to describe symbols geometrically and structurally in maps. In map processing tasks, the shape descriptors and morphological operators described in Section 3.2 are often combined and adjusted to tune the recognition process to the properties of the document of interest. Symbol recognition in maps – in particular in manually drawn maps – is challenging due to their graphical properties in general and the intrinsic meaning and characteristics of symbols in comparison to other documents, such as technical drawings (Cordella and Vento, 2000; Lladós et al., 2002). Traditionally, symbol recognition – also in map processing tasks – can be partitioned into statistical and structural approaches (Lladós et al., 2002) and the distinction from other recognition tasks such as character recognition (see below) is blurred. Note that this section focuses on the main efforts of recognizing singular symbols in maps; the case of composite objects or symbols is reviewed separately in the next subsection (Figure 18).

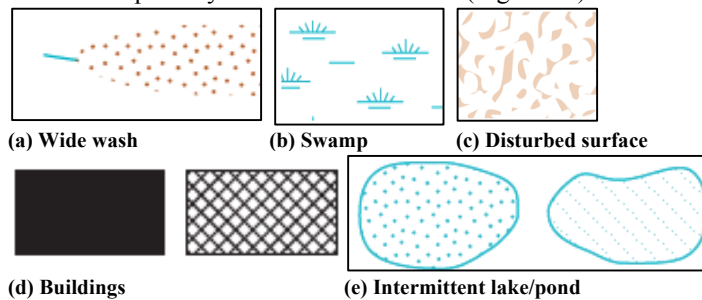


Figure 18 Some examples of singular (bottom) and composite (top) features typically found in maps (from USGS Topographic Map Symbols)<sup>6</sup>

A few so-called knowledge-based systems have been developed for map processing tasks where knowledge is derived from the map of interest or its legend in order to improve the

<sup>6</sup> Credit: U.S. Geological Survey (USGS topographic map symbols)

recognition process. For example, Samet and Soffer (1998) generate shape descriptors from the inverted images of individual symbols in a map; and by creating a library of training sets of geographic features, they developed a legend-driven geographic symbol recognition system with high recognition rates. This innovative, statistical, pattern-recognition approach is limited by the time-consuming training and learning processes and a high degree of map specificity. Myers et al. (1996) focused on the problem of overlapping information in complex color maps and developed a verification-based approach using various knowledge bases of geometric (or shape) descriptors for improved recognition in USGS topographic maps. This was tested on complex wetland symbols.

Template matching, as explained earlier (Section 3.2), represents another knowledge-based recognition method. For example, Yin et al. (2001) describe a supervised probabilistic template matching technique to extract road lines, characters, and symbols in Chinese road maps. Frischknecht and Kanani (1998) develop a hierarchical template matching approach for text and symbol extraction from modern topographic maps. In this approach they weight critical areas within templates differently (emphasize or de-emphasize) thus improving the geometric description of the symbols of interest. Maderlechner and Mayer (1995) apply correlation-based template matching to detect symbols in Bavarian land register maps using explicit knowledge manually derived from the map legend, which makes this method highly map specific. Finally, Reiher et al. (1996) describe a symbol recognition system similar to the others described here but based on Hausdorff distance between symbol templates and the image; furthermore they employ neural networks for their recognition process. The system is reported to be robust in detecting symbols of different scales and orientations.

Several studies on map symbol recognition have used morphological operators and the results are often input to compute shape descriptors. For example, the feature extraction method described by Dhar and Chanda (2006) for various types of symbols (trees, grass, crop fields) in topographic maps applies initial noise removal, thinning, and skeletonization steps. They then compute attributes such as the Euler number (to define holes) and the Rutovitz connectivity number based on the skeletonized data. Erosion/dilation techniques have been used in combination with region growing for gap filling by Bessaïd et al. (2003) in order to extract building symbols. For the extraction of final building contours they use chain coding (Freeman-coding) of contour points. This procedure browses contour pixels until there are no more neighbors or it reaches the starting pixel. The number of identical directions followed by the value of direction (Freeman direction) is recorded and the result of this vectorization is written into a text file. This produces a high degree of compression compared to the original image files.

In a number of studies shape descriptors are deployed without prior use of morphological operators. For example, in a multi-angled parallelism (MAP) algorithm for multi-directional symbol recognition from topographic maps, Yamada et al. (1993) use a re-formalized and parallel version of the generalized Hough transform without changing morphological properties of the objects of interest. Miyoshi et al. (2004) utilize a combination of simple and complex geometric descriptors for building extraction from scanned topographic maps without prior morphological operations. They identify limitations when symbols are merged with other map features such as roads. In an attempt to extract forest symbols from a historical topographic map, Leyk and Boesch (2009) describe existing shapes in the local neighborhood of a pixel also without prior morphological processing. These shapes are then evaluated by their similarity to shapes that are graphically defined as typical for the symbol of interest. As a final example, Trier et al. (1997) perform digit recognition in hydrographic maps for extracting symbols such as rock positions, digits, or signs without the use of morphological operators. For symbol recognition they apply size- and orientation-independent elliptic Fourier descriptors of the outer symbol contour and use them as attributes in their statistical quadratic classifier.

Two graph-based approaches for symbol recognition in maps can be found in the recent literature. In an attempt to extract building information, Liu (2002) describes a method for house contour detection in the graph domain using breaking points of house structure; this method is demonstrated for large-scale pictorial maps. After separation from roads and characters this approach shows satisfactory results. A connected component analysis for the extraction of quarters in historical French cadastral maps is based on a neighborhood graph (Raveaux et al., 2008). Post-processing of the results (pruning of the graph) is necessary to improve the recognition results.

Symbol recognition in maps has made significant progress using knowledge-based or legend-driven techniques, graph-based methods, or approaches that use advanced morphological operators combined with shape descriptors. However, most solutions are still map specific and there is a need for more generic solutions in order to reach higher degrees of automation and robustness. The variety of different symbol recognition techniques described above illustrates how documents of different characteristics have been historically processed using different approaches. It is difficult to identify any clear relationships between techniques and types of maps, which may be the result of the rather experimental stage of map processing research to date.

### 4.3 Extraction and Recognition of Composite Features

Composite features consist of different graphic elements whose spatial distribution (or “composition”) and pattern can define higher-level spatial objects of specific meaning. Examples of composite features are dotted or dashed paths (Gamba and Mecocci, 1999), complex line-work (Yamada et al., 1993; Zhong, 2002), or areas whose spatial extent is defined by distributed single symbols such as circular symbols to describe forest areas (Leyk et al., 2006) or horizontal strokes to describe wetland areas (see examples in Figure 18). Processing such composite features in addition to single objects in maps represents a difficult task (Lladós et al., 2002), especially in maps of lower graphical quality.

The recognition of such compositions of single elements or symbols in different document types has traditionally been subject to principles of structural pattern recognition (Pavlidis, 1977; Delalandre et al., 2004). Structural recognition is based on the definition of spatial relations between graphical primitives (context), such as distances and directions. A set of rules is usually derived and applied to identify these complex symbols of interest in an image (Myers et al., 1996; Lladós et al., 2002).

In some map processing tasks, “contextual reasoning” is used to find certain types of objects in the vicinity of an already recognized object (den Hartog et al., 1996; Ogier et al., 2001). In a knowledge-directed image analysis effort, Ebi et al. (1994) demonstrate how recognition can be improved by identifying compositions of structure primitives on symbols of coniferous forest or symbols of dotted boundaries. Similar principles have been used for the extraction of compositions of character strings (Raveaux et al., 2008). Another approach to structural recognition is based on the use of texture patterns in order to classify cartographic area features from maps (DeKruger and Hunt, 1994).

In pursuing similar goals, Gamba and Mecocci (1999) describe a perceptual grouping approach to track discontinuous chains of symbols, which can be conceptualized as composite linear objects in topographic maps. Once individual symbols are extracted based on shape descriptors, Gestalt rules and optimal paths (i.e., shortest distance) are used to determine those symbols that are likely members of the line object and to close identified gaps. Their approach works well and has been used in numerous recognition studies that face similar problems. Finally, Leyk et al. (2006) use iterative sampling within a local search radius around a detected forest symbol to identify other circular objects in close vicinity in historical topographic maps as shown in Figure 19. The spatial distribution of all identified forest symbols (their composition) defines the approximate extent of forest area.

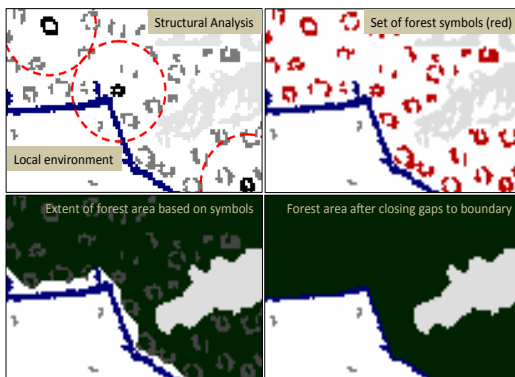


Figure 19 Example of recognition of a composite feature using the method described in Leyk et al. (2006)

Recent research that implemented the concept of composite features has demonstrated that there is great potential for improving feature extraction. Compositions of single graphical elements in maps often define meaningful higher-level objects characterized by their spatial distributions, topological relations, or their spatial context. Nevertheless this concept is still under-used in map processing possibly due to the complexity and computational costs that come with structural recognition approaches. However, solving these problems will be fundamental to efforts of map processing at higher levels of automation for complex map contents. As the above studies demonstrate, the concept of composite features and the few techniques that have been described were reported to be successful in maps of different types and qualities.

#### 4.4 Extraction and Recognition of Linear Features

Much research has been conducted on extracting linear features from scanned maps, including the separation of lines from text (Li et al., 2000; Cao and Tan, 2002; Tombre et al., 2002; Pezeshk and Tutwiler, 2010b), the detection of road intersections (Habib et al., 1999; Henderson et al., 2009), the vectorization of road lines (Bin and Cheong, 1998; Itonaga et al., 2003; Chiang and Knoblock, 2013), the recognition of generic linear objects (Ablameyko et al., 2001, 2002a, 2002b; Bucha et al., 2007), and the recognition of contour lines (Arrighi and Soille, 1999; Khotanzad and Zink, 2003; Chen et al., 2006; Hancer and Samet, 2011; Oka et al., 2012; Miao et al., 2013). Linear feature extraction and recognition techniques usually consist of two steps: the separation of raster layers, which is often done through the image segmentation process described earlier, and the recognition of linear features from the individual raster layers.

Separating the raster layers is often based on histogram thresholding (Figure 20) to extract “raw” road layers. Figure 20 shows examples of well-conditioned maps on the left and the resulting road layers on the right. The top right panel shows an extracted road layer that also has few text labels and both solid road lines and road boundaries. In maps of lower quality, recognition of the linear features is typically based on the generation of centerline representations, which can require the application of different techniques for solid areas of linear features as compared to boundaries of linear features (Chiang and Knoblock, 2013). Most linear-feature extraction techniques expect the extracted layer of linear features to be either areas (Itonaga et al., 2003) or boundaries of linear features (Bin and Cheong, 1998; Habib et al., 1999) but not a combination of both types, which can significantly lower the accuracy of the final vectorization results. In addition, removing parts of or whole text labels from the raster layer of linear features prior to generating the centerlines has been done using text/graphics separation techniques (Cao and Tan, 2002; Tombre et al., 2002; Velázquez and Levachkine, 2004). However, such approaches still require additional repair of disconnected centerlines where the overlapping text is removed (Chiang et al., 2009). Furthermore, subsequent steps of text/graphics separation steps can be impaired when the result of line feature separation contains only pieces of the text labels, as can be seen at the bottom of Figure 20. These remaining text pixels constitute noisy objects that do not follow the criteria of character geometry typically used in text/graphics separation algorithms, such as a character is expected to be a group of small, straight line segments (strokes) (Cao and Tan, 2002).

There are some techniques that exploit more sophisticated processes for extracting the raster layers potentially containing the linear features of interest. Such techniques make it possible to process maps of inferior image quality. As mentioned in Sections 3.1 and 4.1, instead of thresholding the grayscale histogram, these techniques take advantage of the three-dimensional color space (e.g., RGB) and often employ a user-training step. For example, Salvatore and Guitton (2004) apply manual thresholds in the color space to separate the raster layer of contour lines from topographic maps. Khotanzad and Zink (2003) perform this color image segmentation step based on user annotations to extract contour lines from the USGS topographic maps; this method was further exploited by Chen et al. (2006) in order to develop local segmentation techniques, which make it possible to process different topographic maps. In general, techniques that rely on user-trained thresholding in color space perform well on complex maps of inferior image quality. However, user-training processes, such as manually determining color thresholds (Salvatore and Guitton, 2004) or labeling colors of all line-background combinations (Khotanzad and Zink, 2003) are complicated, laborious, and time-consuming.



Figure 20 Sample maps and their road layer extracted with manual grayscale histogram thresholding

Other techniques for line detection avoid relying heavily on user input. For example, Itonaga et al. (2003) exploit the geometric properties of individual map areas to determine road areas (e.g., elongated polygons), but this approach does not work on scanned maps since in scanned maps road areas are not represented as homogenous color areas. Henderson et al. (2009) present another interesting approach that does not rely on user input but rather exploits the metadata of the scanned maps to separate the road layers. In USGS digital raster graphics (DRG) used to build the topographic maps, a set of 13 colors is used to draw the map features, and Henderson et al. (2009) exploit this pre-defined color scheme to isolate the road layer. Table 1 shows the USGS DRG color scheme.<sup>7</sup> Figure 21 shows an example of the USGS DRG. While their approach works well for separating the USGS DRG road layer due to the existence of the color key, it does not work if the color scheme does not exist or is unknown, which is common for most scanned maps. Henderson et al. (2009) indicate that a manual step for separating the road layer is required if the scanned map does not have a pre-defined color scheme. However, this manual step would involve labor-intensive user-intervention before this approach could be applied to a different (scanned) map.

Once the raster layer of roads is separated from the map, raster-to-vector conversion techniques are used for the recognition of linear features from the individual raster layers. This raster-to-vector conversion step searches for elongated binary large objects (blobs) and then generates the centerline representation (skeletons) of the blobs.

One approach to raster-to-vector conversion exploits the detected road boundaries to convert the road areas to vector format. Habib et al. (1999) use edge detection methods to identify road edges. Next, they identify corner points of these edges and determine the centroids of each group of corner points to represent road intersections. False-positive corner-points or T-shaped road intersections can significantly shift the position of centroid points away from the correct locations.

<sup>7</sup> National mapping program technical instructions ([http://gis.ess.washington.edu/data/raster/drg/docs/drg\\_std.txt](http://gis.ess.washington.edu/data/raster/drg/docs/drg_std.txt))

Bin and Cheong (1998) identify the medial axes of parallel road boundaries and link these medial axes to extract and vectorize road data from scanned maps. Linking the medial axes requires manual parameter specifications to ensure the generation of accurate representations of line geometry of road intersections.

**Table 1 USGS DRG color scheme**

Digital Number	Color	Red	Green	Blue
0	Black	0	0	0
1	White	255	255	255
2	Blue	0	151	164
3	Red	203	0	23
4	Brown	131	66	37
5	Green	201	234	157
6	Purple	137	51	128
7	Yellow	255	234	0
8	Light Blue	167	226	226
9	Light Red	255	184	184
10	Light Purple	218	179	214
11	Light Grey	209	209	209
12	Light Brown	207	164	142



**Figure 21 An example of USGS DRG based on a color scheme of 13 known colors to represent map layers<sup>8</sup>**

Other techniques use morphological operators to remove noise (non-blobs), fill small gaps to reconnect broken lines, or determine the centerlines of linear features such as contour lines (Arrighi and Soille, 1999) and road lines (Chiang and Knoblock, 2013). Since morphological operators usually distort the geometry of the original linear features when generating the centerlines (e.g., the road intersections in the top part of Figure 22 are displaced), alternative techniques that employ user-specified parameters to repair the road geometry have been developed. For example, Itonaga et al. (2003) correct the distorted lines around the road intersections based on user-specified constraints, such as the general road width in the considered map. In an attempt to automatically correct the line geometry, Arrighi and Soille (1999) use the centerline endpoints as anchor points to determine the geometry of centerlines. The extremities of the lines are then evaluated for connecting or disconnecting the line segments. Chiang and Knoblock (2013) detect potential areas with geometry distortions and trace line features that are

<sup>8</sup> Credit: U.S. Geological Survey



outside these distortion areas to generate accurate centerlines. The top part of Figure 22 shows the distorted road geometry around road intersections when only the thinning operator is used to extract the road centerlines. The bottom part of Figure 22 shows the correct road geometry after detecting distortions automatically to trace accurate centerlines.

One technique that is reported to be not limited to a specific type of map is described in Bucha et al. (2007). They apply the so-called pixel-force field algorithm (Bucha et al., 2006) to extract the centerlines of linear objects from scanned maps. The pixel-force field algorithm can be applied directly to color maps without the need of a pre-processing (i.e., binarization) step; however, the user needs to manually specify the start and end points of each linear feature, and this requirement significantly limits the automation scale of the pixel-force field algorithm.



Figure 22 Automatic repairing the road geometry (Chiang and Knoblock, 2008)

In a series of publications, Ablameyko et al., (2001, 2002a, 2002b) present an interactive map interpretation system that supports the separation of feature layers in a scanned map based on user-selected colors. Selecting colors can be time consuming since scanned maps with inferior image quality can contain thousands of color values. Once colors are determined this map interpretation system generates centerlines of linear features and contours of area features. The centerlines are then linked to generate the final results. The line-linking step also relies on user intervention, such as to confirm a merge between two line segments or to enforce the continuation of a line.

In order to complete the list of recent efforts it is important to mention that there are a few available commercial products for map processing, such as R2V from Able Software, which is an automated raster-to-vector conversion software package specialized in processing scanned maps. To vectorize roads in scanned maps using R2V, the user needs to first provide labels of road colors or select a set of color thresholds to identify the road pixels. As mentioned earlier, the manual procedure of providing labels of road pixels can be laborious, especially for scanned maps with numerous color values. Also, color thresholding has limitations if, for example, one set of thresholds cannot completely separate the road pixels from pixels of other map features. In addition, the automatic vectorization function in R2V is sensitive to the road width without manual pre-processing and Able Software does not provide details about this automatic vectorization technique. Figure 23 shows a sample map, the road layer, and the road centerlines extracted by R2V. The R2V automatic vectorization function produces small branches on a straight line when the road area is wide.



Figure 23 A sample map processed by the automatic vectorization function in R2V

In summary, recent methods for the extraction and recognition of linear features from maps have largely improved in terms of reducing the required manual effort. However, the resulting vector datasets are still not ready-to-use in a GIS without manual post-processing (e.g., manually identify the missing features). In addition, although incorporating the well-developed vectorization techniques (e.g., Hori and Okazaki, 1992; Rössli and Monagan, 1995; Janssen and Vossepoel, 1997) in the extraction and recognition process can improve the quality of the resulting vector datasets (rather than simply using the morphological operators), a user still needs to manually validate the geometry and topology of the results. To further advance the overall user experience for the extraction and recognition of linear features, we believe the best strategy is to enforce a tight integration between the user training steps (pre-processing), raster-to-vector conversion steps, and the post-processing steps. Tight integration here means the knowledge learned from a previous step can be passed into the next step and help improve the scale of automation in the next step. This allows a map processing technique to produce quality measures for each of the vectorization steps and then use the quality measures to automatically detect the areas that require manual editing. In this way the cost of an end-to-end map processing task can be minimized.

#### 4.5 Extraction and Recognition of Text

Text recognition from maps is a difficult task since the text labels often overlap with other features in the maps, such as road lines, and the text labels do not follow a fixed orientation within a map (Nagy et al., 1997). Therefore, the document structure analysis components in traditional OCR techniques often do not work well on maps (Mao et al., 2003). In addition, depending on the quality of the original map, not every scanned map is a good candidate for text extraction and recognition. Raveaux et al. (2007 and 2008) extract the text layer and identify individual text strings on a set of historical French cadastral maps. They first perform an anti-fading algorithm for restoring the faded colors in the historical maps. Then they use the expectation maximization (EM) algorithm to select the best color space from a set of color components (e.g., red, green, and blue for RGB or hue, saturation, and lightness for HSL) and then apply edge detection based on the chosen color space to identify individual connected components in the image. Finally they classify the connected components into text features by detecting nearby connected components that are similar in size. Figure 24 shows a sample of the French cadastral map where the text labels are broken and faded.<sup>9</sup> While Raveaux et al. overcome the difficulties to extract individual text strings from historical maps with poor graphical quality, they were not able to automatically process the identified text strings and further recognize the string characters.



Figure 24 A French cadastral map from the ALPAGE (AnaLyse diachronique de l'espace urbain PARisien: approche GEomatique) project. Red rectangles show faded labels.

<sup>9</sup> The ALPAGE project ([http://websig.univ-lr.fr/alpage\\_public/flash/](http://websig.univ-lr.fr/alpage_public/flash/))

Some text recognition techniques are highly specific to the type of map or the graphical representation of text elements. For example, Fletcher and Kasturi (1988) and Bixler (2000) assume that lines and text are not overlapping, which does not apply to most scanned maps. Chen and Wang (1997) utilize the Hough transform to group nearby numeric letters to identify straight numeric strings in scanned maps. They use a set of font and size independent features to recognize the numeric strings, which makes their approach specific to these numeric characters. Velázquez and Levachkine (2004) compute four imaginary lines of orientation (V-lines) that follow the main orientations of map text to separate straight text labels from graphics. They then recognize the text labels with artificial neural networks (ANN). Their method can handle slightly curved text labels by dividing a curved label into blocks of straight labels and then apply the V-line approach. This approach does not depend on the geometry of a single connected component but it is not clear how curved labels are identified automatically.

For processing multi-oriented text, more general techniques exploit shape descriptors. Usually, sets of such descriptors are computed from character training samples and then utilized for pattern matching (or template matching) to recognize the characters in scanned maps. Deseilligny et al. (1995) compute rotation-invariant descriptors to identify multi-oriented text strings. Adam et al. (2000) compute descriptors based on the Fourier-Mellin transformation to compare the target characters with the trained character samples for recognizing text labels in scanned maps. Pezeshk and Tutwiler (2010a) produce artificial training data (i.e., a set of generic character images) from a set of initial training data using a truncated degradation model. They then recognize the map characters using two hidden Markov models with 10 states trained for each character class. The truncated degradation model helps to reduce the manual effort of generating training data. However the user still has to generate an initial training set of character images for each font type. These methods (Deseilligny et al., 1995; Adam et al., 2000; Pezeshk and Tutwiler, 2010a) require a considerable amount of training and user intervention for each input map and thus have limited applicability to other types of maps.

Another line of research on text recognition relies on text/graphics separation and subsequent recognition of the separated text strings. Li et al. (2000) use a novel integrated approach to separate text from lines and recover overlapping characters. They identify the feature layers and text labels using connected-component analysis and extrapolate the feature layer (i.e., extend the linear objects in the feature layers) to identify and remove the lines that overlap with characters within each identified text label. Figure 25 illustrates this technique. The identified lines are extrapolated based on linear continuity to identify the pixels that are shared between the lines and text. Instead of assigning the overlapping pixels to either lines or text strings, they assign the pixels to both line and text, which prevents disconnected lines and broken characters and results in a high recognition rate. However, this method does not work for curved lines or text labels. Other text/graphics separation techniques are based on the geometric properties of the connected components in the text layer. Cao and Tan (2002) decompose the connected components into line segments and use a size filter to recover the character strokes that touch the lines. These text/graphics separation methods described here rely on manual work to prepare the separated text strings for optical character recognition (OCR), such as manually rotating individual strings to the horizontal direction (Cao and Tan, 2002).

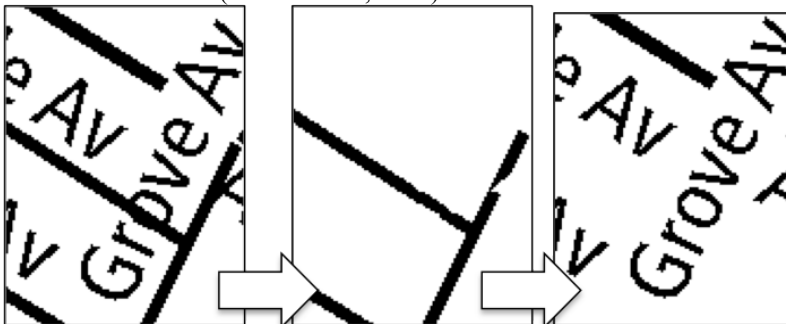


Figure 25 Extrapolation of road lines to recover overlapping characters

The process of automatically rotating individual text strings to the horizontal direction as input for OCR is critical since most OCR packages achieve the best results with horizontal strings. Poudroux et al. (2007) apply connected component analysis followed by string analysis using parameters dynamically generated from the geometry of the connected components to identify string objects in the scanned maps. They then render the identified strings horizontally for character recognition using the average angle connecting the centroid points of the components in a string, which can be inaccurate when the characters have different heights or widths.

Chiang and Knoblock (2011) present a more general training-by-example approach that only requires a small user effort for text recognition in heterogeneous raster maps. Their approach exploits a few examples of text areas to first extract text pixels. Then they automatically expand text areas to locate individual text labels using cartographic labeling principles (e.g., the font size of a single text label will be consistent across the entire label). Next they use a robust skew detection method based on morphological operators (Najman, 2004) to determine the orientation of each string and automatically rotate the strings to a horizontal orientation. Then they use commercial OCR software to recognize the rotated, horizontal strings. Figure 26 shows an example of the automatic orientation detection technique. For a given string, they generate 60 rotated strings by rotating the string clockwise from 0 to 180 degrees with a 3 degree increment. They then apply the closing and erosion operators on each of the rotated strings. Since a horizontal string has the largest number of character pixels near each other, horizontally, the orientation of the string with the largest number of remaining pixels after the erosion operator is searched; an example can be seen on the right side of Figure 26.

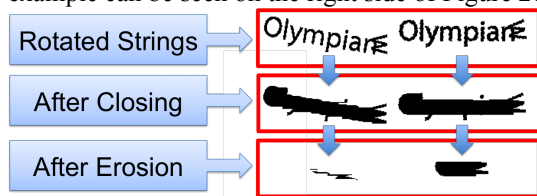


Figure 26 Automatic string orientation detection (Chiang and Knoblock, 2011)

Other text recognition techniques include additional (or ancillary) information for identifying areas of text labels in the map images. Gelbukh et al. (2004) extend the algorithm described by Velázquez and Levachkine (2004) by exploiting additional information from a toponym database, linguistic dictionaries, and the spatial distributions of labels of various font sizes in a map to detect and correct errors introduced during the processes of text recognition. Myers et al. (1996) generate hypotheses about the potential characters in each text label and the locations of these text labels using a gazetteer. They identify text zones in the scanned maps by detecting and grouping short length patterns in the horizontal and vertical directions. The identified text zones are then verified based on the hypotheses generated from the gazetteer using a keyword recognition technique that detects the presence of possible text labels based on whole text shape within the text zone. The auxiliary information (e.g., gazetteers) used in these techniques is usually not easily accessible for map images.

These recent text recognition systems incorporate the underlying cartographic principles for map labeling into their text recognition procedures (i.e., build special document-structure-analysis techniques for maps) to achieve the best results. However, these text recognition systems are map or language specific and are independent from the final character recognition process (consider OCR as a final, separate process). A key challenge here is how to build document analysis rules based on generic cartographic principles and tightly integrate these rules into the document analysis components in the state-of-the-art OCR systems.

#### 4.6 Interactive Map Processing Systems

Since maps can be quite noisy and there is a lot of variation between maps, it is difficult, if not impossible, to fully automate the processing of maps. Thus, a number of systems exploit efficient interactive map processing techniques where the user provides some input to help in the recognition process. Two basic approaches have been used in various studies. The first approach

allows a user to provide sample inputs to guide the extraction of the layers. The second approach allows the user to provide input to repair or improve the layers after they have been extracted. We will review each approach in turn.

A significant challenge in map processing is the variations in how layers are represented from one map to the next. One way to address this challenge is to allow the user to provide examples of the layer or layers that a user wants to extract from a map and use the examples to learn how to extract the layer(s). This has been done using several different methods. In the work by Wise (2002) on extracting soil maps, the user provides a seed pixel for each soil layer and the system uses that seed pixel in a flood-fill algorithm that adds additional pixels if they are adjacent and within some threshold of the RGB value, hue, and brightness. The approach was successfully used to extract layers represented by dithered patterns of different colors, but they recognize that the results could depend on which seed pixel was selected for defining the threshold value. In the work by Bessaid et al. (2003), they extract the layers from four-color maps and the user provides examples of each of the four colors (brown, black, green, and blue) since the actual colors vary from one map to the next. In the work by Chiang and Knoblock (2013), they incorporated user input to identify multiple colors that comprised the road lines in scanned maps. The user selects a single point in the center of a road (as shown in Figure 27) and the system would then detect the road lines based on a Hough transform (Duda and Hart, 1972) for each color. When the majority of the detected Hough lines are near the point that the user selected, the system assigns that pixel color as a road color. This allows the system to determine all the colors that comprise a road line using only a single point selected by the user. Chiang and Knoblock (2011) exploit a similar technique for determining the color of a text layer. The user provides an example of a text string and the system uses the dominant pixel color to extract the text layer.

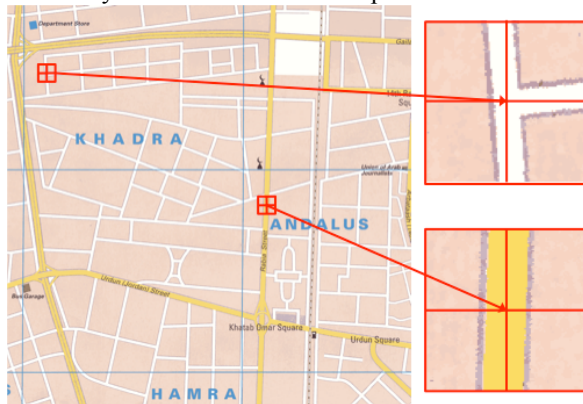


Figure 27 User provides examples of road colors by selecting points in the center of segments

Since maps can be noisy and complex, a related challenge is extracting the layers when there is missing information, overlapping features, or disconnected lines. A number of systems have provided the ability for a user to interact with the system to correct the extracted layers (Suzuki and Yamada, 1990; MapScan, 1998; Ablameyko et al., 2001; Esri ArcScan<sup>10</sup>). The capabilities of these systems are all quite similar in that they allow a user to interactively correct, add, or reject vector lines. Ablameyko et al. (2001) present a set of techniques that focus on connecting broken vectors by allowing the user to specify either two vectors to connect or the length of a sequence of vectors to connect. This addresses a common problem in map extraction where the vector layers are broken due to the overlap with other layers. The other work that is particularly notable is MapScan for Windows (MapScan, 1998), which provides an extensive set of editing operations for dealing with extracted map vectors. In particular, the tool set provided by Mapscan includes the usual operations for adding, deleting, moving, and splitting nodes, as well as operations for adding, deleting, and connecting segments. However, Mapscan is a commercial system and the details of the techniques used are not available. While these interactive approaches are useful for

<sup>10</sup> <http://www.esri.com/software/arcgis/extensions/arcscan>

processing a single map, the user interaction steps need to be repeated for each input map and hence they do not scale well (in production) when there are a large number of maps to process.

Instead of building map processing systems that are specifically tailored to a particular map type, using interactive map processing techniques provides a general approach that makes it possible to process a wide variety of map types. The existing systems described above already demonstrate the generality of using interactive approaches. The remaining challenges are twofold. First, we need to develop interactive techniques that minimize the user input and utilize that input to build end-to-end systems for extracting and recognizing features. Second, we need to develop systems that learn from the user input so that more of the processing can be automated over time.

#### 4.7 Georegistering Maps

There are numerous maps, especially historical maps, that lack the metadata describing the details of the map location, datum, and projection used to create the map. In order to address this limitation and make use of the data extracted from these maps in a GIS environment, researchers have worked on various techniques to automatically georegistering a map. Commonly, there are three steps in the process of georegistering a map. The first step is to extract a set of reference features from the map that can be used for georegistering the document. The second step is to find a set of control point pairs that relate the extracted features with another georeferenced dataset. This is the most difficult step to automate and in many commercial products (e.g., Esri ArcGIS) this step is performed manually. The third step is to then use this mapping to transform the map through rubbersheeting or conflation (Saalfeld, 1993) so that the map is aligned with other geospatial data. Figure 28 shows the overall approach to georegistering a map.

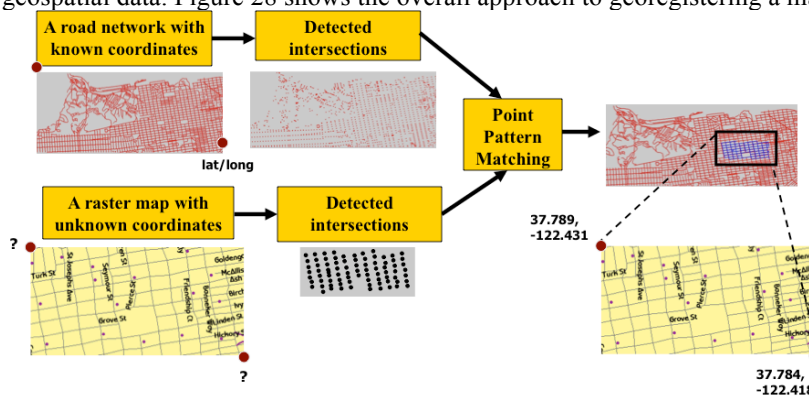


Figure 28 The process of georegistering a map with unknown coordinates

In the first step, the features that are typically extracted from a map for georegistration are a set of road features such as a set of road intersections (Chen et al., 2008) or the entire road network (Chiang et al., 2009), as described in Section 4.4. Road features are often used because they tend to be graphically stable features that change infrequently (current roads in Europe often follow the same paths as the original Roman roads).

In the second step, the task is to determine the precise geolocation of the extracted features by comparing them against an already georeferenced dataset (“reference”). The georeferenced dataset is typically an accurate road network in vector format often from a current, digitally produced data layer. If the map to be processed already has some basic geolocation information (e.g., projection and geodetic datum used), then this is a relatively straightforward matching problem between the features extracted from the map and the georeferenced dataset. However, the more general case is a map with limited or no geolocation information where the problem is to find a small set of features extracted from a map and match them with a large set of georeferenced features in a large road network dataset (called an asymmetric matching problem (Li, 2009)). This problem has been solved in several ways, depending on the assumptions made about the map. Chen et al. (2008) developed an approach that assumes the rotation of the map is known and then finds the translation and scale of the map using an efficient point pattern-matching algorithm (called GeoPPM). The Chen et al. approach is robust to noise and can deal with large numbers of missing or extraneous intersection points, which means that the technique works well on historical maps,

which typically have fewer intersection points since there were typically fewer roads. More recently, Li (2009) developed the SIPPM matching algorithm, which maps the points and their relationships into polar coordinates to provide a technique that can support the mapping with rotation in addition to translation and scale. Their results show that they can map the features on a map to a georeferenced dataset with tens of thousands of points in less than 6 seconds, although the approach may be less tolerant to noise. At the conclusion of this step, these algorithms will produce a set of control points between the locations of the extracted features from a map and the corresponding features in the georeferenced dataset. These control points can then be analyzed to provide the precise geocoordinates, scale, and rotation (in the case of SIPPM) of a map. In addition, the complete set of control points provides a detailed mapping between the two datasets that can be used in the next step.

In the third step, the problem is to actually modify the map so that it aligns with the corresponding georeferenced dataset. This is particularly useful for either overlaying a map on top of an image or improving the alignment of an extracted vector layer from a map with other spatial layers. This step is based on a technique called conflation developed by Saalfeld (1993), which addresses the problem of how to merge two vector maps and their features. In this approach, a map is partitioned into a set of triangular regions using Delaunay triangulation. Delaunay triangulation is used because it maximizes the angles of the triangulations, which reduces the possible distortion introduced in this process. Using these triangular regions, the map or map layer can then be rubbersheeted to the georeferenced dataset so that the two layers are aligned (as shown in Figure 29). In the case of a raster layer, the map would be stretched to align with the other layer; in the case of a vector layer, the vector geometry would simply be updated based on the alignment of the triangles.

In general, the work described above has shown that it is possible to both find and exploit control points to automatically register a map even when the metadata describing a map is missing. However, these techniques still assume that the general location of the map is known and that there exists a reference dataset for that region. An interesting challenge is to build a reference dataset for the whole world and develop techniques that can automatically register a map to a location anywhere in the world and determine the correct metadata for that map.

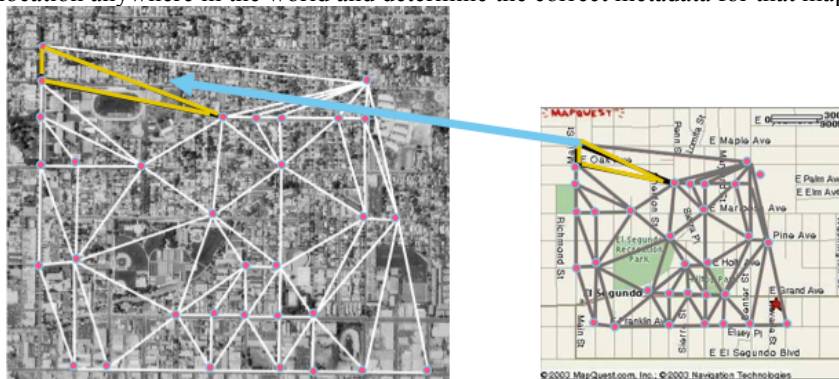


Figure 29 Rubbersheeting a map to an image

## 5. CHALLENGES AND OPPORTUNITIES

As seen in this article, there has been a significant amount of interest in and research on map processing over the years. Existing research efforts have been scattered over many organizations and countries, have addressed a wide variety of issues, and have been published in many different venues. The authors hope that this article will provide a more integrated view of the large body of work that has been conducted. Past research has typically focused on specific map types, because the research is often driven by the need to extract the data from a specific set or series of maps. While much progress has been made on solving numerous problems in map processing, there are many, many problems left to solve. Furthermore, we believe that the ability to extract and georeference the data in maps will unlock a wealth of information that has many applications, including constructing new maps, building better and more detailed gazetteers, performing

historical research about areas that have changed over time, and conducting medical research on links between man-made features and diseases.

Given the history of scattered funding and the narrow focus on specific map types, the question is how to accelerate the progress in the area of map processing. We believe this can be best achieved by encouraging researchers to make their software and datasets available. This will allow other researchers to build on the current state-of-the-art instead of having to re-implement each component themselves. The availability of datasets also means that researchers can then directly compare their techniques against other algorithms and evaluate their techniques on maps that have been processed by others. If researchers make their software available under open source licenses, it also means that we can begin to put together integrated systems that combine the best algorithms, which will then provide a set of tools that can be used by others for extracting data from their own maps. As has been described in this survey, it is difficult to draw direct linkages between certain techniques and types or qualities of maps. Map processing still depends on the expertise of the analyst to choose an appropriate technique for a particular extraction task depending on the type and quality of the map document at hand. Thus, currently there is no unified or generic map-processing framework that would make it possible to select the best-performing techniques and methods for map processing work for various kinds of maps. However, if the community can be better integrated, a systematic understanding of existing solutions can be developed and evaluated to provide the basis for an initial framework in the near future.

Beyond the issue of developing a more integrated community, there are also several areas of specific research that we want to highlight as deserving more attention. First, processing maps is hard due to the complex overlapping data provided in many maps. Thus, we believe it is especially important to develop interactive techniques that reduce the user effort in map processing and allow users to apply their own expertise to extract, verify, and even correct the extracted data. By developing efficient interactive techniques, we can better exploit the knowledge and human abilities for understanding map representations and possibly integrate learning processes to improve the systems. Second, there is a vast amount of historical data captured in maps that could have a wide variety of uses, but often the historical maps are the hardest documents to process. So we believe there should be more focus and more research funding directed to the problems of extracting data from noisy maps. Third, little work has addressed the problem of the provenance, accuracy, and reliability of the extracted results. As map-processing research comes into its prime, there is the opportunity to extract a great deal of information from maps. As a community, we need to record the provenance of these extracted data, develop techniques to estimate the accuracy, and provide methods to quantify the reliability of the generated spatial data.

#### **ACKNOWLEDGEMENT**

We thank Dr. Reid Priedhorsky for his work on preparing the scanned images in Figures 4 and 5. We also thank the anonymous reviewers for their helpful suggestions.

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