# Advanced image processing for maps graphical complexity estimation

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**Abstract.** During the centuries the main problem with mapping was to obtain the sufficient and reliable source data. At present an appropriate selection of the desired information from the deluge of available data causes some difficulties, hence often maps are overloaded with information and thus very complex. Complexity exerts an impact on readability and effectiveness of cartographic representations and for this reason has been the cartographers' object of interest for many years.
A variety of measures of map complexity were introduced. Each of them addresses different map types and uses different definitions of complexity. Therefore, in many cases, measures make use of various totally different characteristics of the investigated map. In the article a novel approach, based on digital image processing techniques, was introduced. The proposed method of graphical load determination is based on dual stage map image processing utilizing wavelet transform and statistical image filters. As the result the map of graphical load directly corresponding to image complexity is obtained.

**Keywords:** maps complexity, complexity measures, digital image processing, wavelet transformation

## 1. Introduction

In the second half of XX. century a new type of society, information society, was developed. In this society the information, including spatial information, plays a vital role. Modern techniques, facilitating data acquisition, collection and processing, have contributed to development of this society. An availability of large amount of data induces to transfer the possibly rich information by means of map. It often results in overloading the cartographic products, hence they become less communicative and difficult to read.
This situation is well illustrated by the example of city maps, which are among the most complex cartographic presentations as they present areas of the greatest concentration of different kinds of forms of human activity

arising from the civilization development. Conveying these specific features on the city maps leads to the problem of selecting the most relevant elements of content in terms of user's needs, since presenting all objects and their characteristics is impossible if the plan readability is to be kept. The application of modern technologies allowed finding a method that enables to determine the complexity of city maps by means of formal indicator.

## 2. Complexity as a map property

Complexity has been the cartographers' object of interest for many years, as it influences readability and effectiveness of cartographic products. Complexity results from a number of symbols on the map, their diversity and the distance between them (density). Complexity may be consider as interaction between these elements relating to two fundamental map's aspects – syntactic and semantic, hence it corresponds to two complexity aspects – visual and intellectual complexity (MacEachren, 1982). The intellectual complexity is mainly determined by the amount of presented information, the character of its presentation, processing level and the classification method as well as number of classes. Even if the map graphics is appropriately selected and objects presented on the map are legible enough, the user may have difficulties in understanding its content if the amount of presented information is too high (Huang, 2002).
The visual complexity results from spatial diversity of visual map structure and depends on degree of extensiveness, generalization and the degree of visual variable order. The visual complexity can be regarded as the opposite to the readability. Wingert (1974) proved empirically that the high image density (overloaded with details) significantly reduces the spatial structure information extraction accuracy. Bertin (1967) described readability as the ability to distinguish the variables from the background and considered that it is affected by graphical density, diversity and resolution connected with the number of symbols, their size and proportions, whereby graphical density was regarded as the most important factor.

## 3. Visual map complexity testing methods

The maps complexity as an objective feature can be studied exclusively at the visual level since only at this level it is possible to separate subjective and objective layers, hence perform justified comparison. In the initial stage of research on the visual maps' complexity most of the works were concerned with the thematic maps in respect to which it was possible to use a metrics that allowed quantifying their complexity in a simple way. According to MacEachren (1982), a number of polygons, edges and nodes

on the map largely reflects its visual complexity. Muller (1976) applied such a complexity determinant in his works on choroplet maps. The results of his works partly reflected the result of previous studies on visual complexity carried out by Gattrell (1974), who noted that the coefficients characterizing the visual complexity should be inseparably related to such map features as the number of point signatures or the line length defining their boundaries.
The meaning of measurable nodes, edges and links between the elements on the map was deeply studied by Egenhofer (Egenhofer et al, 1994). The lines and the nodes were also crucial for Ebi (Ebi et al, 1992) and Ilg (1990) in the studies on images complexity and the possibility of their reconstruction via the automatic digitization process. Mersey (1990) proposed the calculation method estimating graphical complexity similar to MacEachrens' (1982) utilizing the theory of graphs and based on the weighted number of edges on the map. In Dietzel's works (1983), the graph theory was also applied. The experimental studies of Murray and Liu (1994) should also be quoted. They took advantage of geographic information systems in which data is displayed in the form of graphs, which resemble maps. It turned out that the graphical map complexity should be defined taking into account its spatial variability, and not only simple measures such as number of lines or number of particular type of surface objects. Basing on the aforementioned works McCarty and Salisbury (MacEachren, 1982) developed a measure, which allows determining the complexity of contour maps. The similar indices taking into accounts the spatial distribution of map graphical density were worked up by applying the fractal dimension (Burrough, McDonnell, 1998) and the method of spatial autocorrelation (Bonham-Carter, 1994).
Entropy is another very promising quantitative measure, which allows determining the graphical load of the analyzed map (He et al, 1997). That measure has a direct connection with the map information content and is connected with the attempts to characterize quantitatively transmission of information through the communication system. The works on the mathematical background of transferring the information by the communication system and determining its information content with the use of entropy were performed by Shannon and Weaver (1949). A serious drawback of Shannon and Weaver method, which Li and Huang (2002) pointed out, is the lack of possibility for consideration of spatial distribution of objects. Therefore Liu and Huang postulated that complexity measures should also take this aspect into consideration and opted for the coefficients such as Thiessen polygon. The most active researcher of entropy measurement applications in cartographical practice was Bjørke (2003). Taking advantage of useful information concept, he showed how the changes of symbols used on the maps, their accuracy and estimation of disorder can affect the effectives of map drafting and perceiving process. Data compression technique (derived from IT) is another very interesting

approach to the problem of controlling map visual complexity (Coveney, Highfield, 1995).
Diversity of the above described measures of map visual complexity is a consequence of diversified applications of individual measures and different understanding of what the complexity is. Therefore, in many cases the measures make use of various, totally different characteristics of the investigated map. However, since none of these measures may serve for automatic determination of complexity of such graphically complicated objects as city maps, a novel approach was needed for these applications. For that purpose digital image processing techniques have been proposed and successfully applied by the authors.

## 4. Description of the method

Each map (including city maps) may be treated as a 2D distribution of intensity. Therefore, digital image processing techniques may be used to evaluate graphical density. Each image may be represented by a two-dimensional $f(x,y)$ function, where $x$ and $y$ are coordinates in the map plane. Value of the function at every $(x,y)$ point represents intensity or gray scale level at that point (usually denoted as DN - digital number – Gonzales, Woods, 2002). If all $(x,y)$ coordinates and $f(x,y)$ function values are coded by finite sequences of discreet numbers, the resulting collection of numbers may be called digital image. Hence digital image is a finite collection of elements characterized by their location and intensity (pixels).
In digital image processing techniques the processing path, leading to certain results, consists of various mathematical operations performed in strictly selected sequence (Pratt, 2001). Measurements based on processing of information contained in images are often basic sources of experimental data. Therefore one usually strives to define useful objects in the analyzed image (discriminate useful information against spurious one e.g. background) as accurately as possible. This is usually done by locating edges, evaluating areas with unique brightness, hue or texture distributions (Russ, 2007). Various combinations of the above features may be used in more complicated cases to unanimously identify searched objects. Types of measures used to analyze entire image or some of its fragments (individual features) determines the number of the required image processing operations, their types, and order of application.
Automatic determination of graphical density (number of signatures) is hardly possible. Therefore authors of this work have introduced the graphical load notion as an indicator of graphical complexity of a city map. Graphical load is the number of graphical elements per unit map area. That measure is related to the number of graphical elements. Not only it directly reflects map complexity on a synthetic level (indicating points where

objects are close together), but indirectly also takes into consideration map complexity at the elementary level, since it reflects the degree to which individual map elements are complicated. That way it represents city map complexity more accurately. Human mind perceives not only the number of separate elements, but also their complexity (Forsythe, 2009).

Because automatic determination of objects in a raster image (direct determination of graphical density) of a map is impossible, the value of density and its spatial distribution were defined indirectly by specifying graphical load. It was defined with some approximation by using special estimator suggested by the authors. The best way to approximate location of objects in a particular area of a map is to define their edges. The location of edges is indicated by a sudden change of intensity between pixels of an image. The information on background and object fill (in most cases uniform for each object), might be omitted in calculations. It results from the fact of particular perception of an image (2D matrix) by computer systems, in which every point of the matrix (pixel) is represented by single numerical value. If other pixels with identical values around the examined pixel can be found, this means that spatial signal is invariable and does not carry any useful information (Gonzales, Woods, 2002).

The procedure of calculating edges is a common technique used in digital image processing. The advantage of this method is the possibility to show unequivocally objects in images in which the background visually blends with searched objects. Determination of the object edges from the image is a relatively simple numerical procedure. It utilizes the fact that the edge of the object is represented by a sudden change of intensity of surrounding pixels.

Two identical images displaced with respect to each other by one pixel and then subtracted is the easiest way to determine the edges of objects. Due to the possibility of appearance of arbitrary spatially oriented edges in the image, this procedure should be performed twice – individually for $X$ and $Y$ direction. The similar result may be obtained by means of image high-pass convolution filtering with the specially selected filter masks (Pratt, 2001). The Prewitt and Sobel filters with the 3x3 window size are typically used. A larger window size is rarely used. The calculation speed is the advantage of calculations using the convolution operations while its susceptibility to the halftone character of printed maps is the drawback. The high frequency intensity noise always present in the scanned images is also considered as the disadvantage (the random distribution of intensity unrelated to the objects occurring in the image). The halftones as well as intensity noise are most visible in the digitized images of city maps. Therefore, in order to calculate the edges distribution from the images the authors decided to use one of the modern image (signal in general) analysis techniques the continuous wavelet transform.

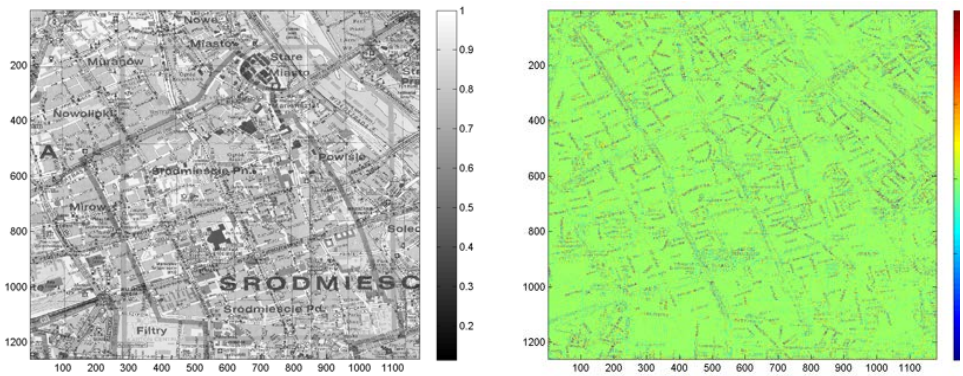
In general, wavelet transform may be regarded as a correlation (comparison) of the analyzed signal with the so-called mother wavelet function. The mother (basic) function is scaled and shifted along the signal in the process of transformation. It must be noted that only a single mother function (of some defined shape) is used during the single transformation. The transformation produces a collection of $W(a,b)$ correlation coefficients for each wavelet scale $a$ and each shift $b$. Wavelet scale $a$ is directly adjusted to the range of possible values of the analyzed signals spectrum, whereas shift $b$ is directly related to the length of the signal. It follows that one-dimensional signal is transferred into two-dimensional array of $W(a,b)$ coefficients. Collection of $W(a,b)$ wavelet coefficients is called scalogram. Each coefficient with $(a,b)$ coordinates is a measure of correlation between the analyzed fragment of the signal and the wavelet of the given scale: a high positive value means a tight correlation between both functions. If two-dimensional signals (like digital images) are analyzed, wavelet transform produces three dimensional arrays $W(a,b,c)$, where $a$ is the scale of the wavelet, while $b$ and $c$ are image pixel coordinates along two orthogonal directions.

In this work, however, distributions of $W(a,b)$ correlation coefficients were utilized in different manner. If shape of wavelet mother functions is correctly selected, the distribution of the $W(a,b)$ coefficients may unanimously indicate location of edges between objects, while background and object fills are removed (discriminated) in the transformation process automatically. For the calculations performed within this work the Symlet 8 wavelet mother function with three different scales (2, 3 and 4) was applied. All calculations have been carried out in the MATLAB environment. The environment is optimized to perform matrix operations, therefore it is very well suited to processing of images that are in fact two-dimensional matrices.

With respect to the high-pass convolution filtration technique described earlier, the wavelet transform technique has one significant advantage: by adjusting de-composition scale of the applied wavelet one can produce results independent on thickness of lines in the image; moreover, intensity noise is effectively reduced. Standard high pass convolution filtering is sensitive to line thickness often indicating them as the additional edges. Since both techniques (convolution filtration and wavelet transform) perform calculation only in one direction (even if the analyzed signals are two-dimensional), each analyzed image was transformed twice successively in vertically and horizontally directions. The two resulting edge maps were next merged into a single 2D map. Merging procedure was done through simple function of searching maximum absolute value for each pixel in the respective horizontal and vertical edge map and next choosing the higher one to put in the resulting map. In the resulting map the sign of the edge value taken from the direction edge map was preserved. Original city map

fragment and single combined 2D map of edges are shown in Figure. 1. The edge values in figure 9 are represented either by positive or negative values, since edges in the picture are either rising or falling. The appropriate value depends on edge height. For the greatest positive and negative heights dark red and dark blue colours in the edge map is used respectively. The background information, which covers most of the map canvas, is represented by the zero value in the edge map (light green colour).

a) b)




Original city map fragment Combined 2D map of edges

**Figure.1** City map transformed in horizontal and vertical directions to create map of edges

It is possible to estimate the graphical density in the specified area, by evaluating the distribution of the object edges in an image. It is intuitive that the more edges occur in the examined area, the greater its graphical density. Therefore, it seems that the summation of pixel values in the designated edge maps of the specified area should properly approximate the number of edges. However, in the case of proposed algorithmic solution is not possible. It is caused by the specificity of the obtained edge maps that take the values symmetrical with respect to zero. Therefore, summation would give us random results, uncorrelated with the number of objects in the area. If the area consisted of an even number of edges, half of which represented by positive numbers and the other half by negative numbers, their sum would be oscillating around zero. Such situation might occur for different, even number of edges. Therefore, in this study authors proposed to use different measures showing changes of the number of edges in the selected area and then treat these values as a graphical load estimator. For that purpose the standard deviation and the entropy of the values representing edges in the selected area were calculated. Both measures strictly indicate the level of diversity of the processed data. As a result two-dimensional map containing the graphical objects density distribution

(graphical density map) is obtained. Diversity of the values obtained reflects the graphical load in the analyzed area.

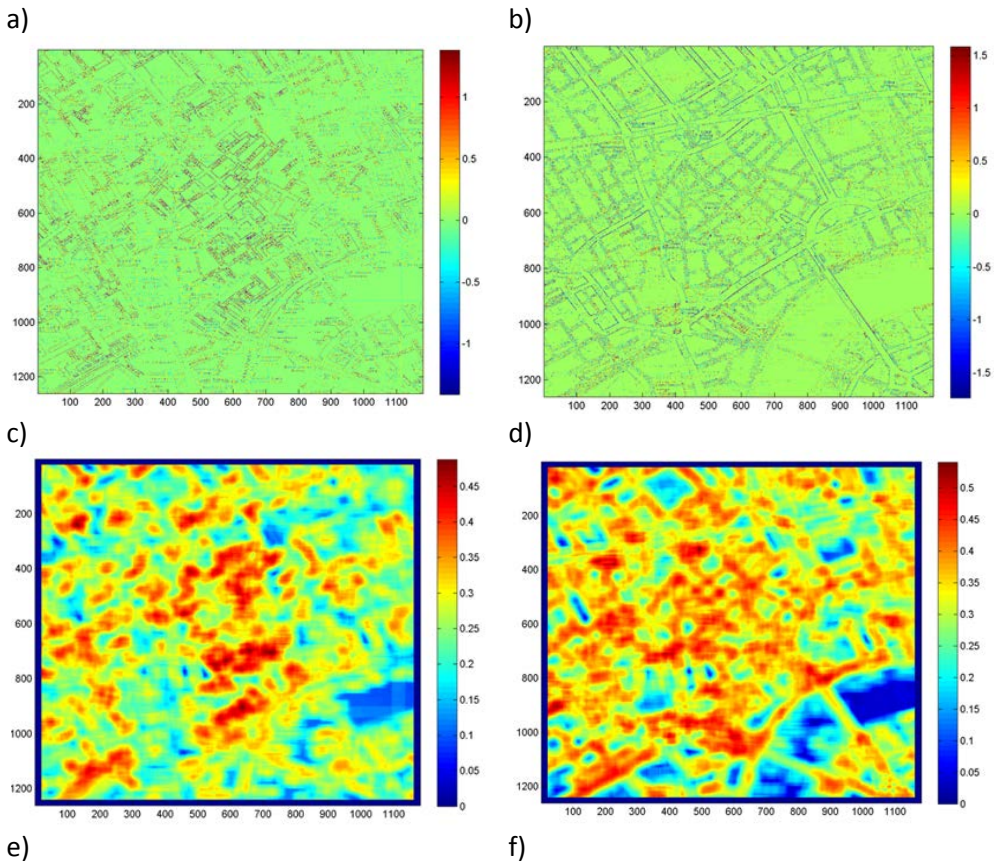
## 5. Results

Obviously, a map must be available in a digital format if its graphical density is to be analyzed by means of a digital image processing techniques. Therefore fragments of different city maps corresponding to downtowns of large cities have been digitized and stored as RGB bitmaps. The data were then converted by two different means: to 8 bit greyscale bitmaps and to hue component from the HSV format. The former format was required by the used digital image processing technique. Since all hue components were taken into account while converting RGB images into greyscale ones, no image useful information was lost in the process. HSV colour space (hue, saturation, value) on the other hand is often used by people, who are selecting colours (e.g. of paints or inks) from a colour wheel or palette, because it corresponds better to how people experience colour than the RGB colour space does. In the study's authors compared calculations of graphical load from both types of maps in order to check which one carries more trustful information. As a reference density estimator the data compression technique was used. Originally derived from IT, it provides very interesting approach to the problem of controlling map visual complexity (Coveney, Highfield, 1995). Unfortunately it returns information on the image complexity a single value. Hence, to compare the results obtained with the method proposed by the authors, for every derived density map the mean density value was calculated. Table 1 shows the correlation coefficients between mean densities obtained using proposed processing method and the data compression technique. As a data compression, Huffman algorithm employed in the JPEG images, with three different quality levels (50%, 75% and 100%) was used.

| | | Standard deviation greyscale | | | Entropy greyscale | | | Data compression | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Wavelet scale | (2) | (3) | (4) | (2) | (3) | (4) | 50% | 75% | 100% |
| Standard deviation HSV | (2) | 0,2464 | X | X | X | X | X | 0,4122 | 0,4197 | 0,4262 |
| | (3) | X | 0,3110 | X | X | X | X | 0,3509 | 0,3487 | 0,3445 |
| | (4) | X | X | 0,3222 | X | X | X | 0,2882 | 0,2791 | 0,2644 |
| Entropy HSV | (2) | X | X | X | 0,5922 | X | X | 0,5742 | 0,5911 | 0,6068 |
| | (3) | X | X | X | X | 0,4628 | X | 0,4993 | 0,4942 | 0,4449 |
| | (4) | X | X | X | X | X | 0,5258 | 0,5542 | 0,544 | 0,4975 |
| Data compressi on | 50% | 0,8317 | 0,8695 | 0,8010 | 0,8916 | 0,8985 | 0,8910 | 1 | 0,9856 | 0,9487 |
| | 75% | 0,8125 | 0,8326 | 0,7536 | 0,9086 | 0,8905 | 0,8662 | 0,9856 | 1 | 0,9808 |
| | 100% | 0,8125 | 0,8086 | 0,7077 | 0,8999 | 0,8656 | 0,8137 | 0,9487 | 0,9808 | 1 |

**Table 1.** Correlation coefficients between mean densities obtained using proposed processing method and the data compression technique

Determination of the standard deviation or entropy of the edge values, and thus the graphical load estimation, is performed for each pixel of the edge map, and the calculations are made while taking into account the surrounding of the particular pixel. A map showing the spatial distribution of graphical density is obtained. In the study, the calculation area of 41 x 41 pixels has been chosen. Such area corresponds to a field of 0.5 x 0.5 cm2 in scanned maps. Size of the calculation window was selected empirically after analyzing the density distributions for differently sized calculation windows. For the windows size used, it was possible to find a compromise between the graphical load range of variation and its continuity in the image. Example of an edge map calculated from the gray scale image and hue component image for the selected city map and the graphical density distribution maps (utilizing standard deviation on entropy filters) determined on their basis are presented in Figure 2.



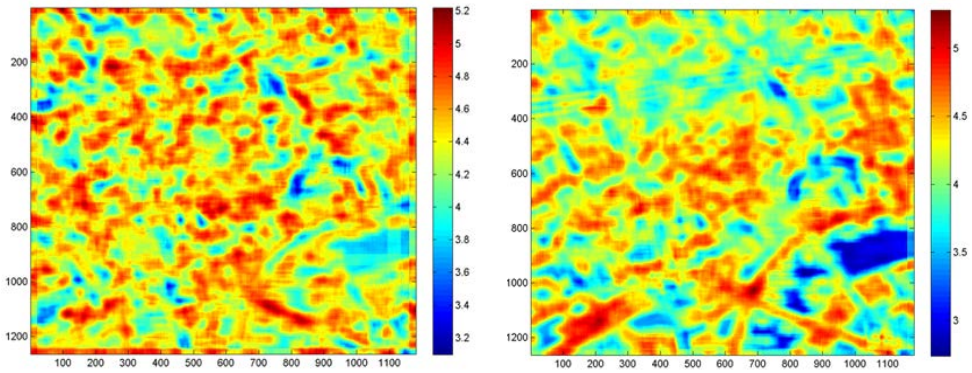



**Figure. 2** a) Edge distribution calculated for greyscale image, b) Edge distribution calculated for hue component image calculated, c) and d) graphical density distributions calculated with standard deviation filter, e) and f) graphical density distributions calculated with entropy filter

## 6. Conclusions

The proposed method of graphical load determination provides comparability of the maps, loaded with various elements (point and line signatures, captions, etc). The results obtained with proposed methods show that gray scale image based density maps are much more correlated to the one proposed in the literature (data compression) than the HSV component image based density maps. Density maps calculated from the hue component of HSV format, are highly susceptible to reprography halftone present in the certain areas of scanned images, thus artificially modify density value. Further studies on the method will include other components of the HSV format as a specific weights used in the calculation in every pixel.

Nevertheless, based on the selected cartographic material analysis, it can be concluded that proposed calculation method allows the quantitative assessment of maps graphical load with a formal index. It should be noted that many of the methods for examining graphical complexity refer to maps certain aspects, while the method proposed in this paper refers to all of the elements on the map and, therefore, refers to an analysis on a higher, synthetic level. It should be added that there is a great compatibility between the visual experience and the level of calculated graphical load (calculated from the gray level images) displayed in the graphical density maps.

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