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Measuring maps graphical density via digital image processing method on the example of city maps

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Abstract. During the centuries the main problem on mapping was to obtain the sufficient and reliable source data; presently, an appropriate selection of the desired information from the deluge of available data is a problem. 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 documents, that is why they become less communicative and difficult to read. This situation is well illustrated by the example of city maps which are the most commonly used and thus the most frequently published cartographic products. Many user groups with different needs as well as preparation to read maps use these high volume publications. Therefore, the maps communication effectiveness problem is of particular importance.
The city maps are the most complex cartographic presentations, because the presented areas are the places with the greatest concentration of different kinds of objects and 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 city map readability is to be kept.
Although complexity has been the cartographers' object of interest for many years, because it exerts an impact on readability and effectiveness of cartographic documents, none of the measures used so far may be applied for automatic determination of complexity of such graphically complicated objects as city maps. Therefore a novel approach was needed for these applications. For that purpose digital image processing techniques have been proposed and successfully applied by the authors. The analysis of the spatial distribution of the objects' edges on the map surface, calculated using continuous wavelet transform, is the basis of the proposed measure. The method allows for comparison of complexity of city maps loaded by different type of graphical elements (point signatures, lines, text, etc.). Extended analyses of selected cartographic materials proved the usability of the method for quantitative estimation of city map complexity via formal index.

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

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1. Introduction

In the second half of 20th century, in the countries where the development of modern technologies was the fastest, a new type of society, so called information society, was developed (Hetmański, 2003). In this society the information, including the one of spatial nature, plays a vital role (MacEachren, 1991). The modern techniques have contributed to that fact which basically improved the acquisition, collection and processing of data. The excessive wealth of acquired information becomes a significant problem (Taylor, 1991). Insofar during the centuries the main problem on mapping was to obtain the sufficient and reliable source data; presently, an appropriate selection of the desired information from the deluge of available data is a problem. 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 documents, that is why they become less communicative and difficult to read.

This situation is well illustrated by the example of city maps which are the most commonly used and thus the most frequently published cartographic products. Many user groups with different needs as well as preparation to read maps use these high volume publications. Therefore, the maps communication effectiveness problem is of particular importance.

The city maps are the most complex cartographic presentations because the presented areas are the places with the greatest concentration of different kinds of objects and 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. Different city maps, which are available on the market, vary in the presented content (Ciołkosz-Styk, 2010), substantive and visual level, applied scales and complexity. Up to now, however, no investigations on city maps complexity were conducted. The available methods of complexity measurement were introduced mainly for choroplet or isopleths maps processing. These methods were providing single value of complexity measure allowing rough comparison of different maps. The authors of this paper were interested not only in the values describing complexity but also in its spatial distribution over city maps canvas. This is why novel complexity index was proposed. It bases on the application of modern technologies (advanced digital image processing techniques) that allowed finding a method enabling determination of the spatial distribution of city maps complexity by means of formal index.

2. Complexity as a map property

Since many years complexity has been the cartographers' object of interest, because it exerts an impact on readability and effectiveness of cartographic documents (Monmonier, 1974). It mainly depends on the number of symbols on the map, their diversity and the distance between them, i.e. their density (Żyszkowska, 1993).

The complexity of the map is the result of interaction between its elements relating to two fundamental map's aspects – syntactic and semantic. It corresponds to two complexity aspects – visual complexity and intellectual (semantic) complexity (MacEachren, 1982; Castner and Eastman, 1985). The intellectual complexity is mainly determined by the amount of presented information (both expressed by means of the number of presented categories as well as the number of elements shown within the presented categories), the character of its presentation, processing level and the classification method as well as classes number. 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 (Bjørke, 1996; Li and Huang, 2002).

The visual complexity (graphical) is the result of spatial diversity of visual map structure. There are following factors which specify this diversity: 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) applied the analysis of visual structure density to study the impact of visual complexity on the map interpretation. He 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 problem of map complexity has been investigated by researchers for a long time because it significantly affects the information obtained by the map user. The studies on the influence of the maps' complexity on their perception, however, only began at the turn of 60's and 70's of 20th century when research methods taken from psychology allowed for the determination of this influence.

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 (Żyszkowska, 1993). The first attempts on determination the maps complexity relied on finding the so called vector measures that allow identifying which of two compared maps is characterized by a greater graphical load (Fairbrain, 2006).

It should be noted that 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 research shows that the map image features mainly influencing created measures of its visual complexity were related to the edges designating contours filled with different colours (areas determined by the choroplet map classes).

The meaning of measurable (countable) nodes, edges and links between the elements on the map was deeply studied by Egenhofer et al. (1994). In this study, they focused on the analysis of characteristic points and lines searching for the relation between them by using the tools available in geographic information systems. The lines and the nodes created by them were also crucial for Ebi et al. (1992) and Ilg (1990) in the studies on images complexity and the possibility of their reconstruction via the automatic digitization process.

Visual complexity of maps was also studied by Mersey (1990). She 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 measures of graph theory applicable to the elements occurring on the maps allowed developing graphical complexity index for maps in different scales. In this index, the average values from the total number of counted objects were included. In the reported works topographical maps and their linear symbols were analysed.

The experimental studies of Murray and Liu (1994) should also be quoted. In their works they took advantage of geographic information systems in which data is displayed in the form of graphs which resemble maps. Their studies show that the time and correctness of the answers given by systems users are not connected with the complexity of entire graphs but rather with the spatial inhomogeneity of their complexity. The answers quality was strictly depended on the cyclomatic complexity of the analysed graph area (not on its overall complexity). In the study, the authors assessed the graphs complexity through the so-called cyclomatic complexity developed by McCabe (1976). These works shed the completely new light on graphical map complexity. 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 account the spatial distribution of map graphical density were worked up by applying the fractal dimension (Burrough and 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 analysed map. It may be applied for both vector (linear) and raster maps (Gattrell, 1977; Knopfli, 1983; 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). Sukov (1967, 1970) applied the Shannon's information theory to the cartographic communication theory in order to measure the information content of maps. Similar studies were carried out by Grygorenko (1973) and Midzio (1972) who made an attempt to define the opportunities to quantitatively assess maps informative function and make attempts to assess their usefulness value.

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. Whereas, the spatial distribution of information has an important meaning, Liu and Huang postulated that complexity measures should also take this aspect into consideration. They opted for the coefficients such as Thiessen polygon (also known as Voronoi diagram). Neumann (1994) used the entropy crate measure based on Thiessen's polygons considering the diversity degree of graph nodes indicating to all possible internal joints on the map (between points, lines and surface marks) receiving a topological characteristic of information map content which is equivalent to the measure of its complexity. The most active researcher of entropy measurement applications in cartographical practice was Bjørke (1996, 1997, 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. Bjørke demonstrated that maps entropy measure can be successfully used in the utilitarian aspect, e.g. during the preparation of dot maps (considerations regarding the weight and size of individual dots), contour maps (considerations regarding the interval's value between contours) or choroplet maps (assistance in determining the appropriate number of classes). Entropy can also be used to verify the quality of cartographic generalization, because its value changes with the generalization of line curvatures and the selection of proper area symbols (Bjørke, 2003).

Data compression technique (derived from IT) is a very interesting approach to the problem of controlling map visual complexity (Coveney and Highfield, 1995). It works best for raster images stored in bitmap files. To store a bitmap means to save the digital values of each pixel of the map (most frequently in RGB channels). Unless some compression technique is used, large volumes of such data result in large size files. Various data compression algorithms (quadtree, run-length encoding etc.) have been proposed in order to limit sizes of the files; they are based on the fact that information stored in a bitmap is usually redundant. Data compression is regarded as a measure of algorithmic complexity, i.e. Kolmogorov complexity, that determines the size (length) of the most concise program capable to generate the desired result.

Diversity of the above described measures of map visual complexity is a consequence of diversified applications of individual measures, and a consequence of 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 the measures may be applied 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. Application of digital image processing techniques to determine map complexity

4.1. Maps as 2D intensity distributions

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 and 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*. Digital image is, therefore, a finite collection of elements each characterized by its location and intensity. Those elements – basic cells of each digital image – are called *pixels*.

Digital image processing techniques use computers to process and analyse digital images. The processing path consists of various mathematical operations performed in strictly selected sequence (Pratt, 2001). Digital image processing techniques are commonly applied in numerous branches of science and technology, where images carry (in an encoded form) some useful information. Those techniques are developed for and utilized in the two following major application areas: (i) modification or enhancement of images in order to improve perception by the users or to facilitate some further processing (printing, displaying, electronic transmitting, storage); (ii) measurements of some image features or parameters coded in the image using some special techniques (Gonzales and Woods, 2002). Measurements based on processing information contained in images are often basic sources of experimental data. Therefore, one usually strives to define useful objects in the analysed 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 analyse entire image or some of its fragments (individual features) determines the number of the required image processing operations, their types, and order of application.

Obviously, a city map must be available in a digital format if its graphical density is to be analysed by means of a digital image processing techniques. Therefore, fragments of city maps corresponding to downtowns of large cities have been digitized and stored as RGB bitmaps, then converted to 8 bit greyscale bitmaps. The latter 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.

4.2. Simple image processing operations applied to determine graphical density

The procedure of city map graphical density determination is very complicated since it should reliably determine all graphical objects within the entire map area. Binarization and segmentation are two commonly used digital image processing operations for the purpose of selecting object from the background. Binarization is based on associating 0 or 1 logical value to each map pixel depending whether the given pixel represents background or an image object. Threshold discrimination is the simplest implementation of that operation: each pixel of intensity value above some selected threshold is automatically qualified as a background pixel or else as an object pixel (Russ, 2007). The threshold may be selected manually or automatically basing on some statistical analysis of histogram of all intensity values in the map. Convention (0 = background, 1 = object or *vice versa*) is arbitrary. Binarization will be successful if the image background (useless information) is relatively constant and its intensity is clearly different than intensity of the objects to be indicated. Slowly varying backgrounds are sometimes allowable. Special adaptive algorithms may successfully discriminate such backgrounds since they calculate and use local background averages in individual small sub-areas of the image (Pratt, 2001). Sample result of a successful binarization performed using simple discrimination against some fixed threshold is shown in Figure 1. In the given example objects (electric parts) have been distinguished very well against their backgrounds, objects geometric shapes have been faithfully preserved.

The next step of digital image processing allowing for automatic identification of image features is segmentation. The segmentation algorithm identifies image regions, in which certain attributes are similar. Pixel intensity is the attribute most commonly used in practice, however, texture or distribution of edges are also used quite often. The procedure does not take into account a context information of the analysed image area, nor classifies the identified segments. The algorithm just splits the image up into segments. It does not recognizes classes of the identified segments, neither their mutual relations. Lack of image segmentation theory is an important fact. So far neither any guidelines have formally been specified how to divide images into segments, nor any standard segmentation method has been adopted. Majority of the practically used algorithms have been worked out *ad hoc*; only some of them gained certain popularity. Therefore no objective criteria to measure quality of segmentation results are available. Haralick and Shapiro (1985) proposed some qualitative estimators that might help

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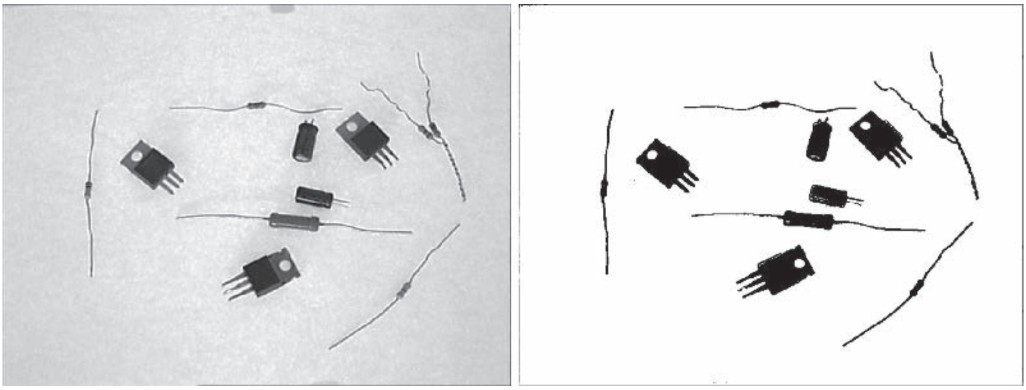

Fig. 1. Results of binarization operation performed using fixed threshold (pictures taken from own research)

to decide whether the segmentation process has been carried out correctly: the selected attribute (pixel brightness, texture etc.) should be homogenous in each of the resulting segments and clearly different in adjacent regions, whereas boundaries between the segments should be straight, regular, and precisely localized.

It is very difficult – if possible at all – to carry out (either automatically or manually) the binarization and segmentation processes on digital images representing city maps. It is a consequence of a very complicated graphical structure of such maps, where very different elements of the map contents may mutually overlap. Examples include lines representing roads that may overlap shapes representing buildings, parks, industrial areas etc. Moreover, point signatures and labels used on every map may conceal other graphical elements, hindering the process of their correct identification in the image or even making that process altogether impossible. The procedure to segment individual image elements and to assign them to individual element groups would be extremely time-consuming and highly unreliable since errors would be inevitable. Results of binarization of a sample city map carried out at various applied discrimination thresholds are shown in Figure 2.

It must be pointed out that classes of features in a city map image might be effectively sorted out using some very sophisticated image processing methods, including multi-step iterative approach, each step of which consists in modification of the image intensity histogram according to some adaptively selected transfer function followed by the binarization and segmentation operations. However, powerful computers and long computational times are required to accomplish such iterative procedures. Additionally, procedure working out for some map usually turns out to be unique in the sense that it does not produce satisfactory results

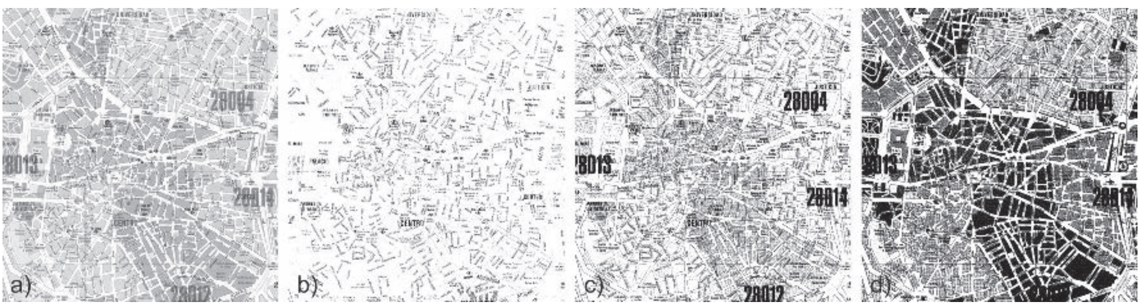

Fig. 2. Binarization of city map: a) digitized fragment; b), c) and d) images after binarization with thresholds 128, 180 and 220 DN, respectively

on other maps due to different pixel intensity ranges and different thresholds that need to be adopted for different feature classes. Such solution is therefore unacceptable – the map analysis method should be much more universal.

4.3. Graphical load

Automatic determination of graphical density (number of signatures) is practically impossible. 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 (Fig. 3).

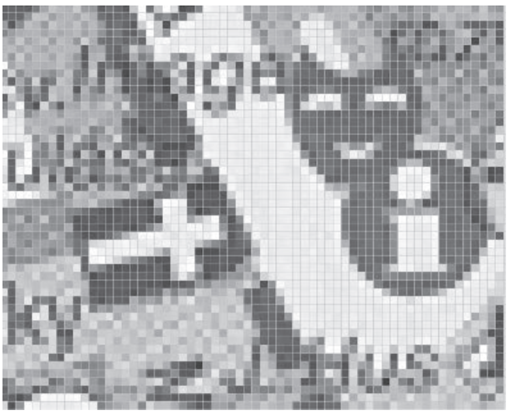

Fig. 3. Church and tourist info symbols are examples of a single signature composed of two graphical elements: bright cross/"I" letter and dark background

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 faithfully. Human mind perceives not only the number of separate elements, but also their complexity (Forsythe, 2009).

4.4. Edge representation of objects

Because automatic determination of objects in a raster image (direct determination of graphical density) of a map is impossible (see section 4.2), 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 and Woods, 2002). An image of exemplary objects with their representation seen by a computer and approximation of their location with the use of edges is shown in Figure 4. The figure shows that distribution of defined edges located in the analysed area unequivocally determines localization of objects.

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. It is clearly shown in Figure 5, where two examples of objects are presented and their edges are determined. It is worth mentioning that in Figure 5a an object and its background are difficult to distinguish, while after defining the edges, it is easy to differentiate the object and the background. From Figure 5b it can be concluded that, despite different colour of those two types of objects, it would be hard to distinguish them (separate the gray cells from white ones) with the use of standard methods of processing images, while using information about the frames enables finding the threshold between different types of objects.

Processing edges spatial distribution of objects located within a city map enables calculating graphical load treated as an estimator of graphical density. The proposed method of analysis of that load allows defining spatial distribution of the searched value of graphical density in city maps

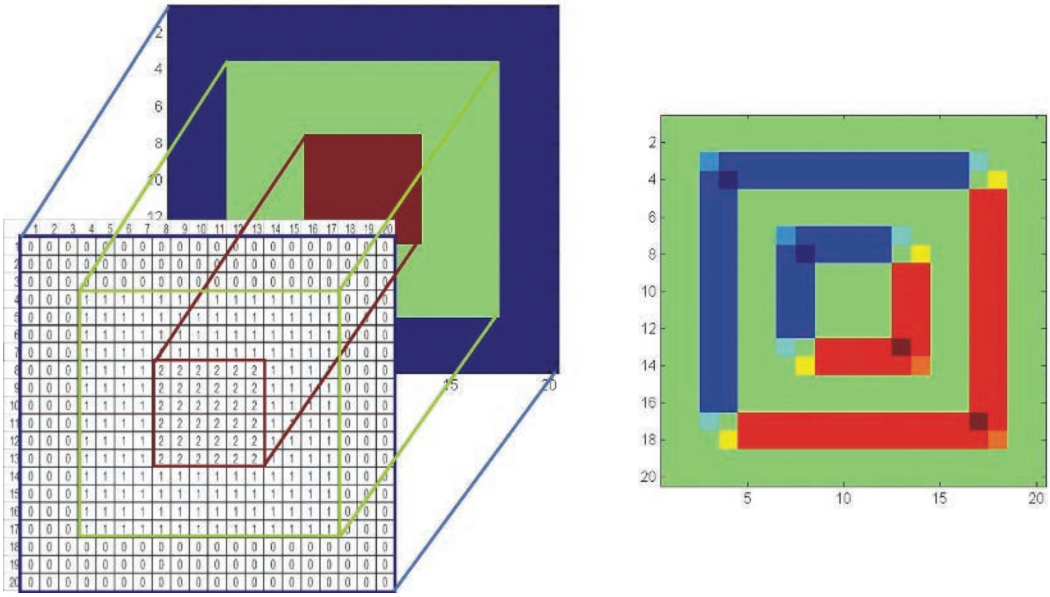

Fig. 4. Exemplary distribution of objects in an image and their representation seen by a computer together with distribution of edges calculated from those objects

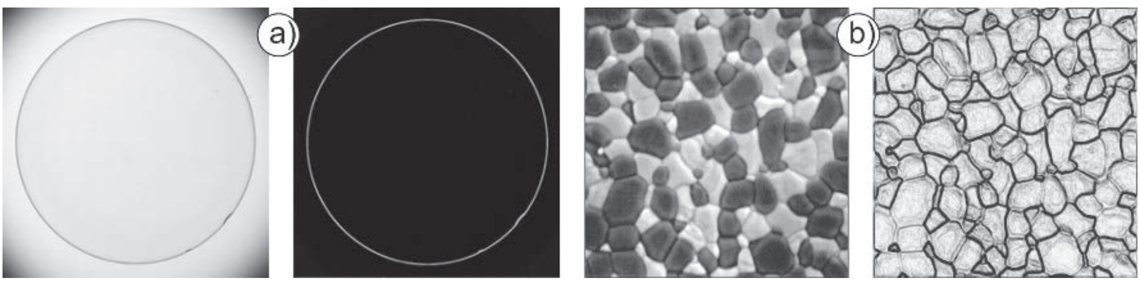

Fig. 5. Examples indicating the advantages of defining edges in image processing (Russ, 2007)

shown in both raster and vector form. To determine the searched distribution of objects edges an advanced image processing techniques employing continuous wavelet transform were used.

4.5. Application of continuous wavelet transform for edges determination

Determination of the object edges from the image is a relatively simple numerical procedure. It uses the fact that the edge of the object is represented by a sudden change of intensity of surrounding pixels. The literature distinguishes four basic types of edges: slope, step, line and roof. The distribution of intensity in all types of edges is shown in Figure 6.

In this study, all kind of point signatures, lines and surface objects have been assumed as the elements of the image. Therefore, in the procedure of determining the edges on the city maps images, all rapid changes of pixels intensity represented by the step type have been considered as the edge.

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 3 × 3 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 raster character of printed maps (raster fulfilment) 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 raster fulfilments 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.

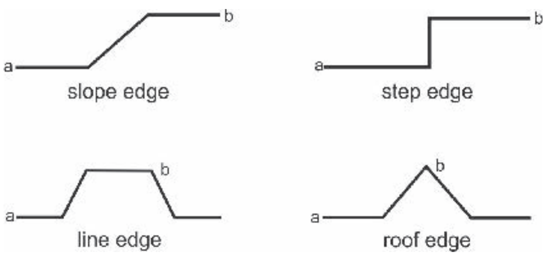

Fig. 6. Types of edges found in digital images

Continuous Wavelet Transform (CWT) is a very attractive signal filtering and analysis technique that allows for searching of local changes of signal parameters (Daubechies, 1992). The continuous wavelet transform was established within the works on the improvement of commonly used and efficient tool used in the analysis of digital images – Fourier Transform (FT). CWT allows processing non-periodic signals which are more often an object of analysis than the periodic ones. The Fourier transform processes a function from a given area in the way that the periodic (frequency) features are displayed. The Fourier transform applied to analysis of images allows determining the harmonics with the specified spatial frequency from the image (Russ, 2007). Each object in the image characterizing by the finite dimensions and the periodic occurrence has a specific spatial frequency which identifies it well. Since Fourier Transform is the global operation (all Fourier transform values are calculated from the entire image), it does not allow for the precise location of selected objects characterized with the specific spatial frequency. Hence Gabor suggested different approach based on the analysis of fragments of the signal modulated by Gaussian function with Fourier transform in order to achieve not only the frequency but also the temporal (spatial) information on the signal (Gröchenig, 2001). This approach is equivalent to the analysis of the local frequency components in contrast to the global analysis carried out by FT. The continuous wavelet transform provides the same feature, however, with significantly increased accuracy of space – frequency location of the signal. Due to this property, the continuous wavelet transform is applied to process the images in optical measurement techniques also in the discrete version (DWT).

Width of the filter applied by the wavelet transform method may be tuned to various spectrum areas, helping to localize signal in both time (location) and frequency (spatial frequency) domains. Thanks to the multi-resolution property, the method provides good spatial resolution both in small scale (within the range of low spatial frequencies), as well as in large scale.

In general, wavelet transform may be regarded as a correlation (comparison) of the analysed 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 analysed 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 analysed fragment of the signal and the wavelet of the given scale: a high positive value means a tight correlation between both functions. If 2D signals (like digital images) are analysed, 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.

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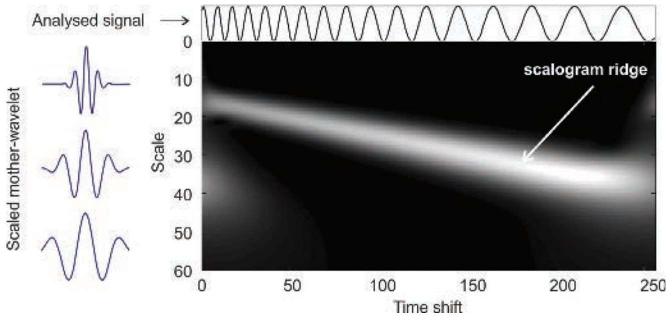

Fig. 7. Example of signal and calculated scalogram for one-dimensional signal

Wavelet transform and calculated scalogram for example of one-dimensional signal are shown in Figure 7.

In Figure 7 sinusoid with variable period is an example of the analysed signal. The two-dimensional matrix of $W(a, b)$ coefficients is shown below the signal (greyscale image). Wavelet shift, i.e. location of the analysed fragment of the signal, is represented on the horizontal axis whereas wavelet scale (spatial dimension – length for one-dimensional signals) – on the vertical axis. The larger wavelet scale, the wider wavelet window with which the analysed signal is correlated. Greyscale shades in the resulting scalogram represent values of wavelet/signal correlation coefficient (for the given scale and position). The brighter shade – the stronger correlation. Collection of the largest values of the correlation coefficients each for certain wavelet shift defines the so-called *scalogram ridge*. It is best to use the scalogram ridge values to inverse transform the wavelet transform back into the original signal. Most commonly wavelet transforms are scaled by some coefficients to enhance some characteristic features of the encoded signal, than transformed back into the signal itself. Since wavelet transform may be described as measurement of similarity of a collection of wavelets (of the same shape but different scales) to the analysed signal, it is best to use wavelet mother function of a shape as close to the analysed signal shape as possible. Sample wavelet mother functions are presented in Figure 8.

Typical application of the wavelet transform technique is to de-compose signal into a collection of wavelet coefficients, then to modify them according to certain requirements and re-combine them into the processed signal form. 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 5 wavelet mother function was applied. All calculations have been carried out in the MATLAB environment. The environment is optimized

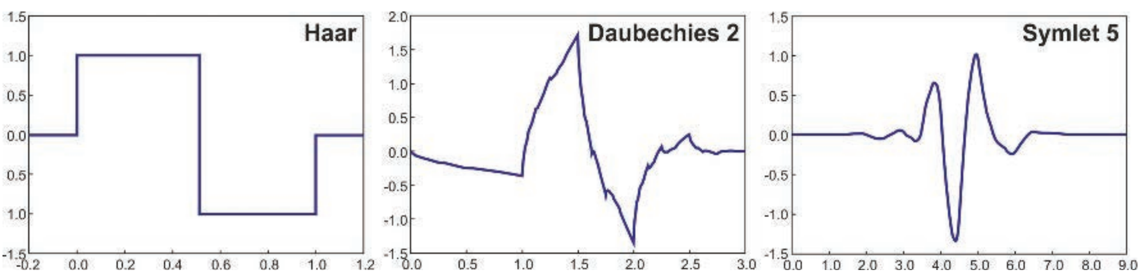

Fig. 8. Sample wavelet mother functions

to perform matrix operations, therefore, it is very well suited to processing of images that are in fact 2D matrices.

With respect to the high-pass convolution filtration technique described earlier, the wavelet transform technique has one significant advantage: by adjusting decomposition 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 analysed signals are two-dimensional), each analysed 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, distribution of edges in the horizontal direction, distribution of edges in the vertical direction, and single combined 2D map of edges are shown in Figure 9. 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).

4.6. Graphical load determination

Evaluating the distribution of the object edges in an image, it is possible to estimate the graphical density in the specified area. 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 due to the specific character of the obtained edge maps that take the values symmetrical with respect to zero. Therefore, summation would give 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. This is shown in Figure 10.

Therefore, in this study, the authors calculated standard deviation of intensity values representing the edges in the given area and treated these values as a graphical load estimator. This deviation is determined at each point of the map on the basis of its surrounding. Thus, a 2D map containing the graphical objects density distribution (graphical density map) on the analysed city map is obtained. For the maps shown in Figure 10, the determined standard deviation values are 0.61 for the map with more edges and 0.31 for the map with a smaller number of edges, respectively. Diversity of the values obtained reflects the graphical load in the analysed area.

Determining the standard deviation of the edge values, and thus the graphical load estimation, is performed for each of the edge map pixel, and the calculations are made while taking the surrounding of the particular pixel into account. This way, a map showing the spatial distribution of graphical density is obtained. In the study, the calculation area of 41 × 41 pixels has been chosen. Such area corresponds to a field of $0.5 \times 0.5\ cm^2$ in scanned maps. Size of the calculation window was selected empirically after analysing 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 for the selected city map and the graphical density distribution map determined on its basis are presented in Figure 11.

5. Conclusions

The proposed method of graphical load determination provides comparability of the maps, loaded with various elements (point and line signatures, captions, etc). Based on the selected cartographic material analysis, it can be concluded that this

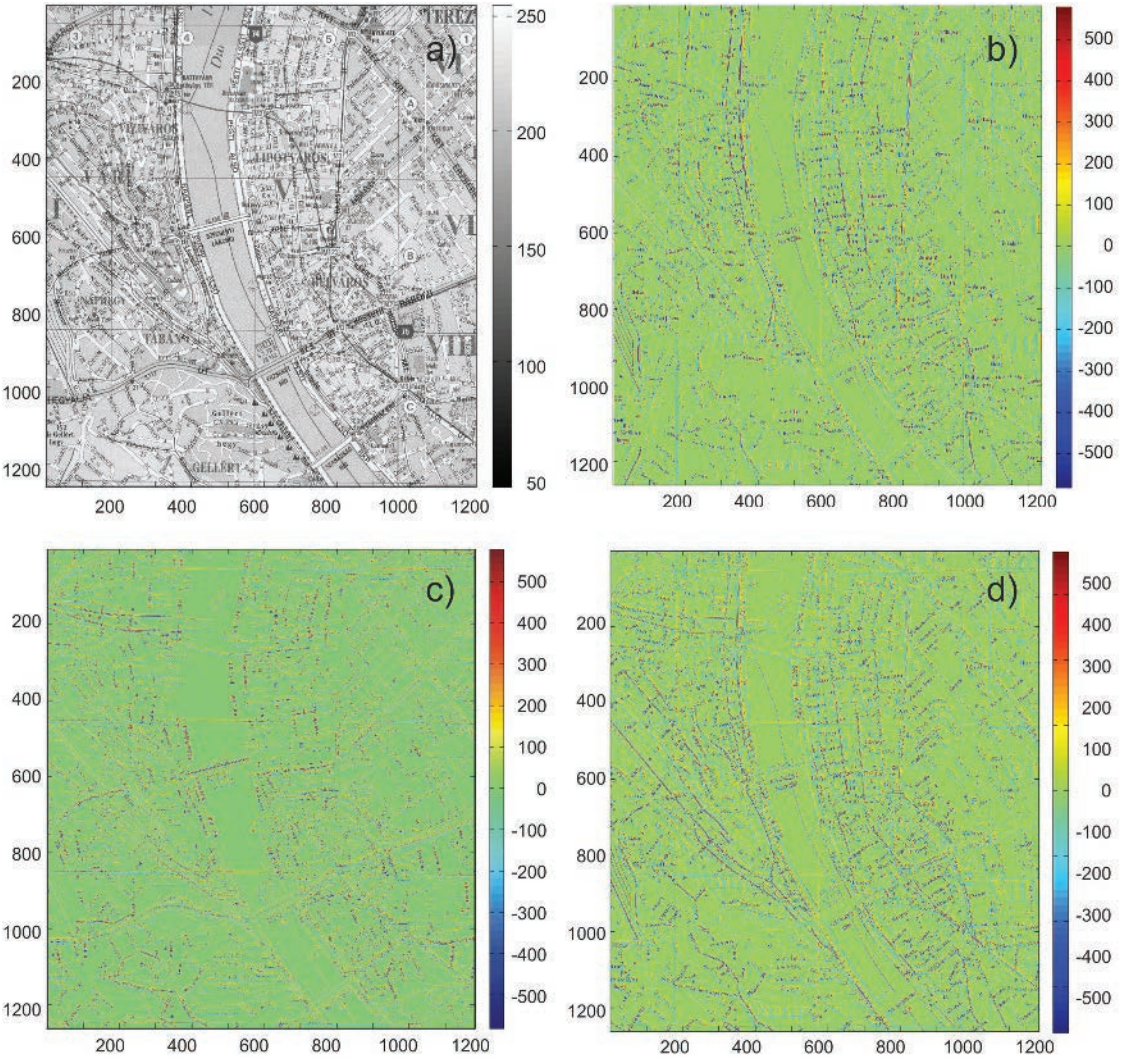

Fig. 9. City map transformed in horizontal and vertical directions to arrive at map of edges: a) original city map fragment; b) distribution of edges in the horizontal direction; c) distribution of edges in the vertical direction; d) combined 2D map of edges

method allows the quantitative assessment of city 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 (for example, data compression method has been tested for presenting topography), 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 displayed in the graphical density maps.

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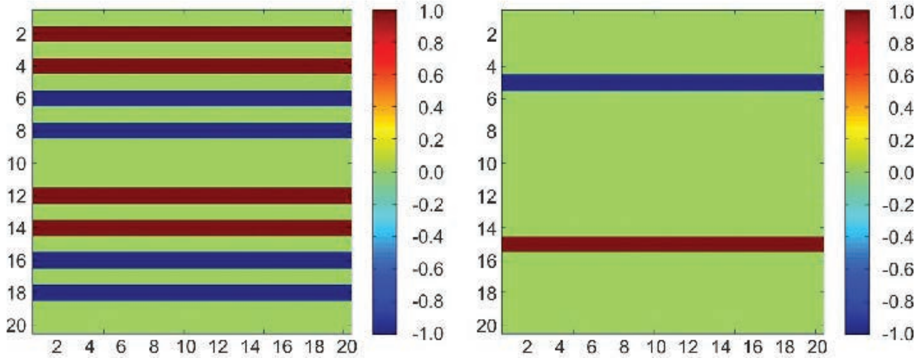

Fig. 10. Example of two different edge map containing even number of edges, hence giving the same result of edge values summation (the sum of the edge values = 0)

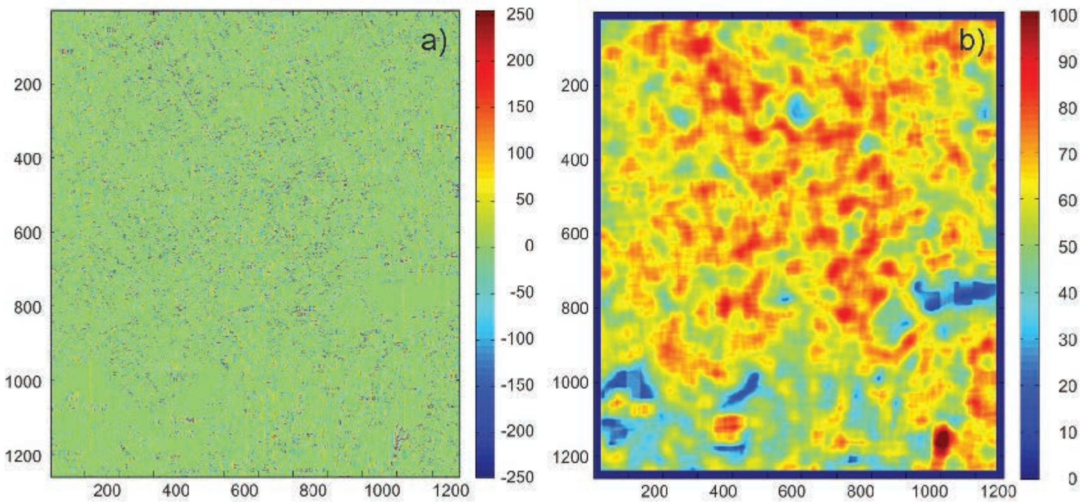

Fig. 11. a) edge distribution calculated for selected city map and b) calculated graphical density distribution

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Zastosowanie metody cyfrowego przetwarzania obrazów do wyznaczania gęstości graficznej opracowań kartograficznych na przykładzie planów miast

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Streszczenie. Przez wieki głównym problemem przy opracowaniu map było uzyskanie wystarczających i wiarygodnych danych źródłowych, natomiast obecnie problemem stał się odpowiedni wybór pożądanej informacji z zalewu dostępnych danych. Dostępność dużej ilości danych skłania do przekazania za pomocą mapy możliwie bogatej informacji. Skutkuje to często przeładowaniem opracowań kartograficznych, przez co stają się one mało komunikatywne i trudne w odbiorze. Tę sytuację dobrze ilustruje przykład planów miast, które należą do najczęściej wykorzystywanych, a przez to również najczęściej wydawanych publikacji kartograficznych. Z tych wysokonakładowych opracowań korzysta wiele grup użytkowników o zróżnicowanych potrzebach i przygotowaniu do czytania map, dlatego też problem efektywności przekazu informacji za ich pośrednictwem jest szczególnie istotny.

Plany miast należą do najbardziej złożonych prezentacji kartograficznych, ponieważ obszary, które prezentują są miejscami największej koncentracji różnego rodzaju obiektów i form działalności człowieka, wynikających z rozwoju cywilizacji. Oddanie tej specyfiki na planie miasta stawia problem wyboru najbardziej istotnych z punktu widzenia potrzeb użytkownika elementów treści, bowiem przedstawienie wszystkich obiektów i ich charakterystyk jest niemożliwe, jeżeli ma być zachowana czytelność planu.

Chociaż złożoność od wielu lat jest przedmiotem zainteresowania kartografów, ponieważ wywiera wpływ na czytelność i efektywność opracowań kartograficznych, to jednak żadna z dotychczas stosowanych w kartografii miar złożoności nie pozwala na jej automatyczne określanie w przypadku tak graficznie skomplikowanych opracowań jak plany miast. Konieczne było więc zaproponowanie nowej metody, pozwalającej na wyznaczanie złożoności graficznej tych opracowań. W tym celu zastosowane zostały techniki cyfrowego

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przetwarzania obrazów. Zaproponowana metoda zapewnia porównywalność map, obciążonych różnymi elementami (sygnaturami punktowymi, liniowymi, napisami etc.). Na podstawie analizy wybranych materiałów kartograficznych można stwierdzić, iż metoda ta pozwala na ilościową ocenę obciążenia graficznego planów miast przy pomocy sformalizowanego wskaźnika.

Słowa kluczowe: plany miast, złożoność, gęstość graficzna, cyfrowe przetwarzanie obrazów, transformacja falkowa