grade correspondence analysis,
image grade decomposition,
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GRADE-SPATIAL PROCEDURE IN GRADE DECOMPOSITION OF MEDICAL IMAGES

The paper describes decomposition of gray medical images. Pixels of the image are assigned with the variable values derived from a neighbourhood of the pixel. Then Grade Correspondence Cluster Analysis is used to order set of pixels according to their grade differentiation and to divide pixels into subsets. Subsets are visualized in separate subimages and regions are extracted on principle of spatial neighbourhood in subimage. Influence of a number of subimages is discussed. Then a new grade-spatial procedure is proposed which combines features of grade similarity and spatial neighbourhoods.

1. INTRODUCTION

The main subject of the presented paper is decomposition of gray level image into regions of similar pixels in medical images such as NMR image. Investigation of more uniform groups of pixels allows to seek hidden structures in the image. An application of statistical method based on Grade Correspondence Analysis is used for pixel gathering. A grade analysis, its models and methods is comprehensively described in [7]. The extensive application of the grade analysis with many useful tools is implemented in application called GradeStat [3]. The GradeStat developed in ICS PAS is used to accomplish analysis of large multivariate datasets resultant from many tasks.

Paper [4] presents some ways of pixels description which convert and adapt gray image into the data table. Pixels are rows of this table. Columns (variables) are originated from gray level of pixel and its neighbourhood. The first variable is simply gray level of pixel. The second variable is its gradient magnitude. Next k variables are built with the aid of thresholds family. Thresholds are constructed in the simplest case as a product of normalizing coefficient, maximal gradient magnitude in the inquired image and successive integer numbers. Variables measure how many of eight neighbouring pixels have magnitudes which differ from gradient magnitude of the pixel less than successive thresholds. In paper [5] the grade differentiation measure of two data tables with equal dimensions is applied. For each variable the table is restored. It has the same size as the image and contains values of this variable. The grade differentiation measure is evaluated for every pair of variables. Measures comparison shows that the number of thresholds and variables can be significantly decreased. Paper [6] describes another simplification which is an effect of neglecting coefficient and thresholds. Variables are gray level or grade magnitudes of neighbouring pixels, ordered for every pixel in non-decreasing sequence. There are some possible differences, for example normalization by gray level or grade magnitude of the central pixel of interest.

Shi and Malik [8] use normalized cuts to a points grouping problem. Image or set of features is represented as weighted undirected graph. Cut criterion is normalized to avoid tendency of cutting single nodes whereas weights involve reciprocal of distance between nodes. Measure used to normalized cut evaluation is defined as a sum of two components: for both nodes subsets cost of removed edges in bipartition is divided by sum of edges between subset and all nodes in the set. Search of optimal partition is formulated as solving eigenvalue problem. Binary indicator vector with dimension equal to the set dimension shows node membership in two subsets. Connection vector indicates measure of total connections for each node. Matrix of weights is formed too. Diagonal matrix is constructed from connections vector. Minimization of normalized cuts criterion is transformed to solution of applied

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eigenvector problem and a second smallest eigenvalue is used to obtain bipartition. Both local and global features are involved in recursive segmentation.

Comaniciu and Meer in [2] describe a kind of mean-shift method. Arbitrary chosen features as pixel coordinates from a spatial domain of the image and any other local information as colour or texture from range domain are mapped into multidimensional space of parameters. Multidimensional space is regarded as an empirical density function with local maxima. Gradient density estimator leads to a formula of difference between weighted mean and a centre of used kernel. Local mean shift vector determines direction of a path converging in the local mode. Paths starting in different points converge in limited number of modes. Basins of attraction in parameter domain form regions in the image domain. Only one parameter is established, i.e. kernel bandwidth which controls resolution. Developed method is versatile and it is also used by the authors in smoothing adaptively preserved salient edges.

Arbeláez et al. in [1] presents mature and complex hierarchical image segmentation. Oriented gradient is established inside a disc with the use of histograms of both halves of the disc. The disc is divided by diameters with various angle orientation. Multiscale approach results from different diameters of discs. Texture is evaluated with the aid of textons which are multidimensional vectors of seventeen filter results. Vectors are clustered using K-means method, pixels are assigned codes of the closest texton. Oriented gradient with discs is applied to such an image. Contour detector is a combination of detectors of three colours and texture and across different diameters of discs. Non-maximum suppression is achieved when the biggest values is selected over all used angles. Globalization of the detector involves spectral clustering in which affinity matrix is built for pairs of pixels within established radius and with the aid of earlier obtained detector values. Solution of eigenvector problem allows in the next step attach n-dimensional vector to pixel and use normalized cuts. The image is then clustered with the aid of K-means algorithm.

Szeliski [9], especially in Chapters 5 and 7, presents entire collection of contemporary segmentation and structure recovering methods, for example, graph cuts which is used to segment anatomical tissues.

Spots greater than one pixel prepared on the basis of grade similarity will be later used in grade or above described methods of NMR images analysis. Development of grade algorithm for medical image analysis gives opportunity to extend solutions of challenging and in time more demanding task. Section 2 includes discussion on influence of clusters number in grade image decomposition. Section 3 introduces new grade-spatial procedure whereas Section 4 describes some details and outlines of future work.

2. GRADE DECOMPOSITION OF IMAGES

A gray image is transformed to the data table which is proper to the following grade analysis. There are no strict limits. Colour images in any colour model and any local features of images are permitted. The other elements than pixels, for example, smaller regions suitably described can be gathered using grade analysis.

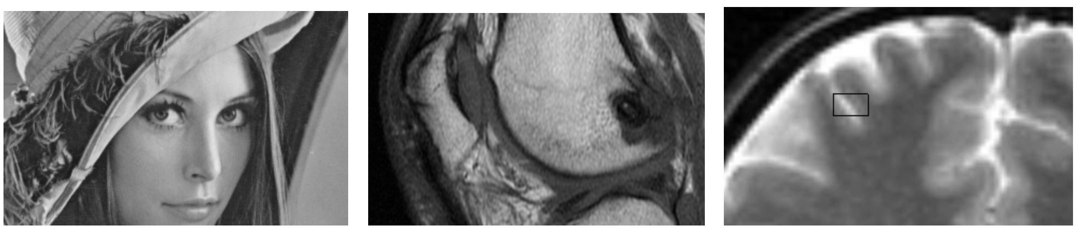


Fig. 1. Images of Lena, NMR knee and NMR brain.

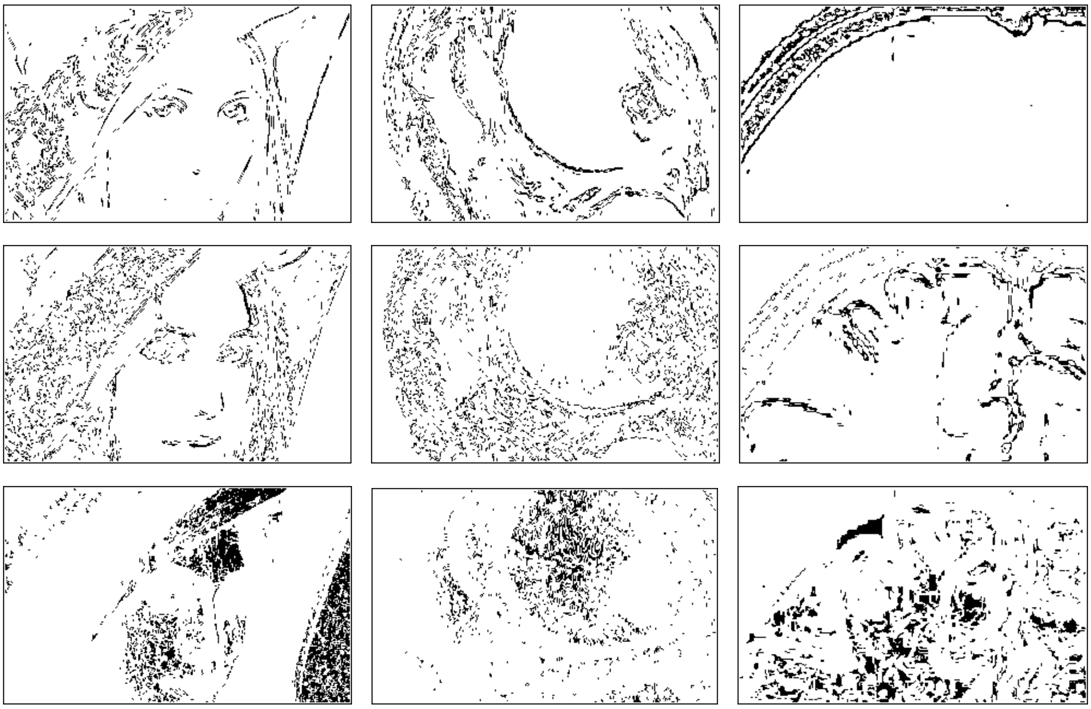


Fig. 2. GCCA image decomposition into 10 subimages. First, second, fourth and tenth subimages are shown.

The gray image is a table of $M \times N$ pixels with attached integer gray levels. Pixels are records in the data table so this table has $M*N$ records. The first value in the record is gray level g_l of the pixel. The second value is gradient magnitude g_m. The next, eight gray values of eight neighbouring pixels g_i, $i = 1,...,8$ are considered. These values form a sequence v_j, $j = 1,...,8$ which satisfies the following property $v_j : v_j < v_{j+1}$, $j = 1,...,7$, e.g. values are ordered in non-decreasing way. The record has (2 + 8) values and the data table is size of $(M*N)$ records $\times (2+8)$ variables. Now the data table is a subject of grade analysis as any other table of numbers. The GradeStat application normalizes each cell by dividing it by a sum of column and a sum of rows. Normalized table is then regarded as probability density function on unit square. The GradeStat reorders rows and columns with the aid of Spearman rho measure of grade differentiation of the data table. The description of used methods and performed operations as well as following partition into clusters is contained in [7]. Rows and pixels are reordered in such a manner that similar rows are placed near each other in the data table. These rows which are different are distant in the data table. The data table is ordered to gain maximal possible differentiation. Then clustering procedure divides sequence of ordered rows into disjoint groups of continuously changing pixels. Pixels which are more similar are in the same cluster. Numbers of pixels in clusters are not equal. These numbers are established by clustering procedure. Procedure tends to increase differentiation measure of aggregated table of clusters after distributing successive pixels to subsets. Each cluster is then visualized in separate subimage and spatial dependencies are recovered.

Figure 1 shows three representative test images whereas Figure 2 presents some of subimages. Additionally, regions of adjacent pixels in 8-neighborhood are extracted in every subimage and single separated pixels are removed, e.g. in the subimage are only true segments assembling at least two pixels.

There is a question of preliminary selection of clusters number. The large number of subimages is difficult to manage as there is no image dedicated version of GradeStat yet. Ten subimages seem to be great enough to show as many as possible significant regions. However, there is a problem of grouping pixels which are in the same cluster. Pixels grouping is performed in the spatial domain, e.g. at an image plane and on pixels lattice. The most important dependency is adjacency of pixels. Pixels are in the nearest spatial neighbourhood but their location in the data table can be pretty far. For example, one pixel is near the top of cluster in the GCA table whereas the second one is near the bottom in this cluster. Both pixels are inserted in the same subimage, they are gathered in the same region due to the fact that both are adjacent in the space domain. However, pixels grade characteristic indicates relative smaller similarity. So these pixels should be indicated as belonging to the different regions.

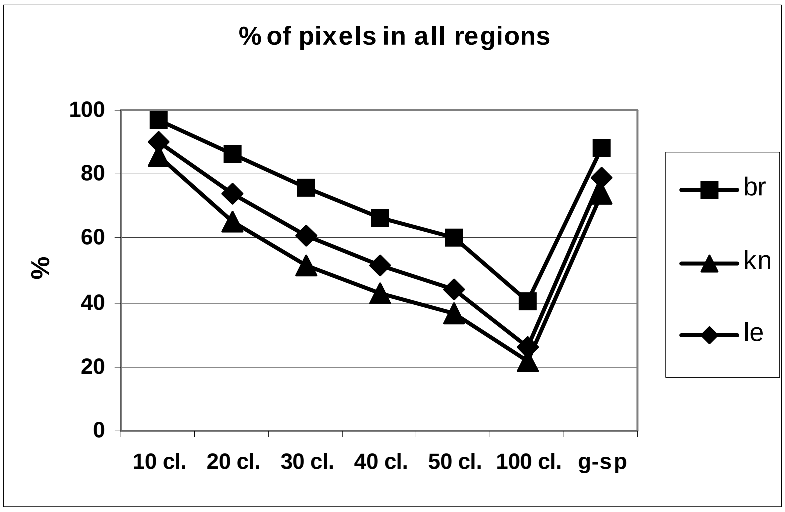


Fig. 3. Amounts of regions obtained with different number of clusters and with g-sp procedure for image of type brain (br), knee (kn) and photograph (Lena - ln) shown in Figure 1.

One of possible solutions is a finer clustering of the data table. If the number of clusters increases, amount of pixels in clusters is less and a distance between first and last pixel in the data table is smaller. The first and the last pixel are much more similar in the meaning of grade differentiation measure. The increase of clusters number results in greater number of subimages. Less pixels belong to each subimage and average density of pixels in subimage decreases so there is more space between pixels. As a result regions are smaller, more isolated pixels appear. Figure 3 shows how many pixels are successfuly gathered in regions. For a division into ten clusters (item 10 cl. on horizontal axis) there are from 80.8% to 96% pixels in all regions (in a whole set of tested images). For twenty clusters such amount decreases and is between 59% and 86.5%. Further clusters increasing causes drastic decreasing amount of grouped pixels. In the case of partition into one hundred clusters some subimages occur with a few isolated pixels and without any region.

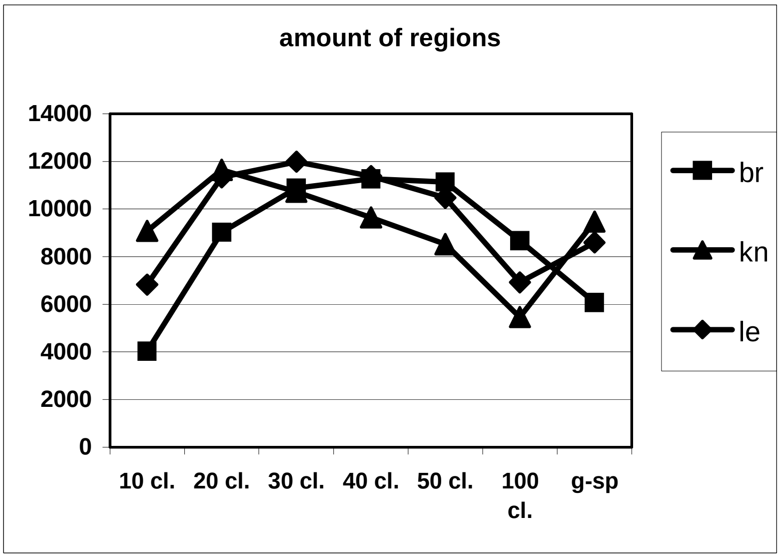


Fig. 4. Fraction of pixels gathered in regions obtained with different number of clusters and with g-sp procedure.

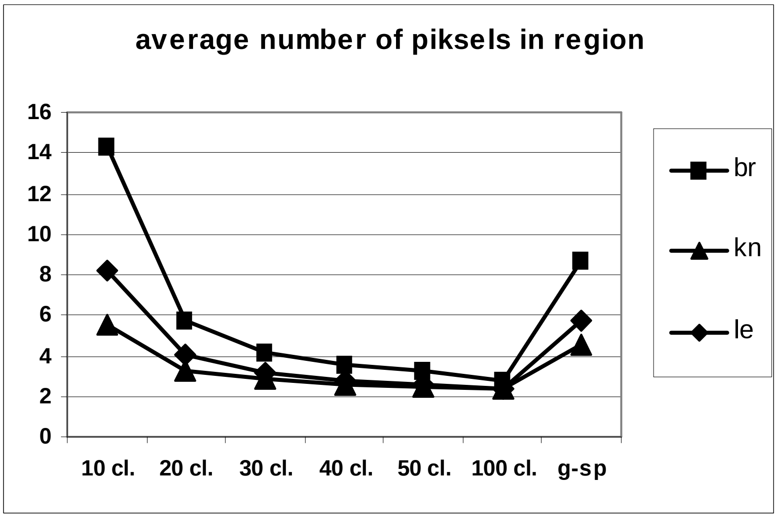
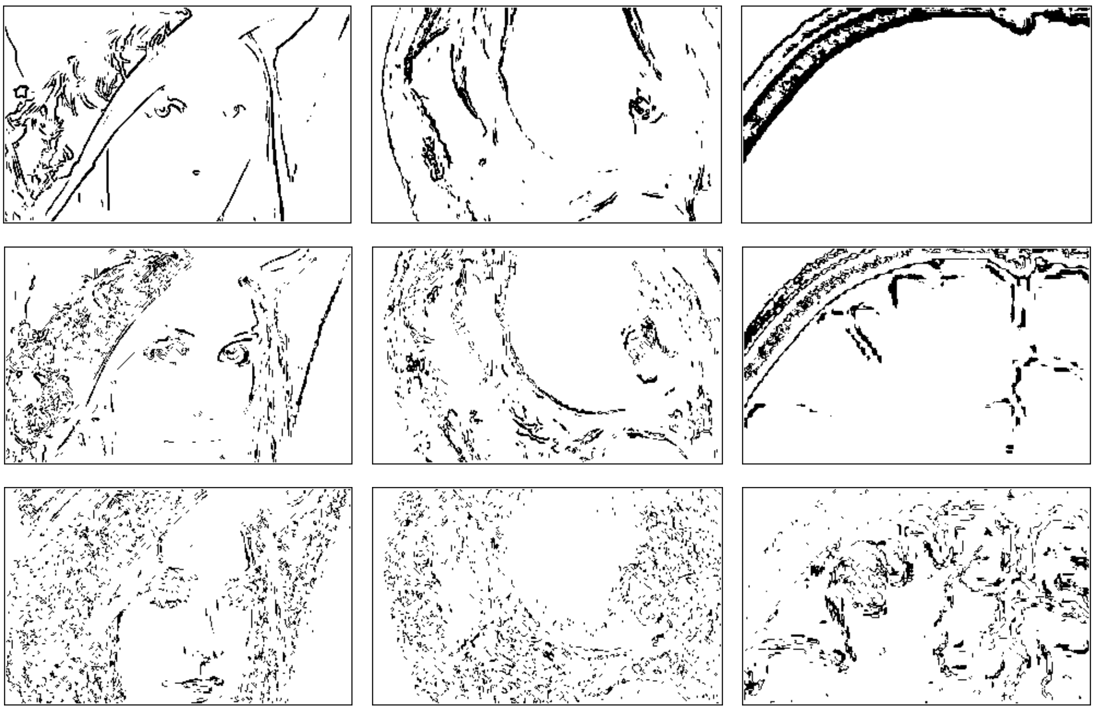


Fig. 5. Average size of region obtained with different number of clusters and with g-sp procedure.

Figure 4 shows dependence of amount of found regions on clusters number. At the beginning, amount of regions grows when the number of clusters increases. It does not mean that if there is more regions at the same time more pixels could be gathered in regions. Figure 3 suggests that size of region lowers due to the fact that less pixels are assigned to regions. If the number of clusters approach to one hundred, the highest tested number of clusters, anyway the amount of regions falls near initial level. Figure 5 confirms this conclusion. (In this figure average number of pixels in region is shown.) The biggest regions occur in the case of ten clusters of the data table and the sizes of regions drastic lower for bigger number of clusters.

3. GRADE-SPATIAL DECOMPOSITION OF IMAGES

Clustering part of the GCCA procedure is smart enough. Procedure does not break distinct structures into different clusters. However, it can connect together into one region completely different pixels as those from the beginning and the end of one relatively big cluster due to pixels spatial proximity. Therefore a grade-spatial procedure (g-sp) is developed which involves simultaneously the grade ordering of pixels and a neighborhood of pixels in the spatial domain in the image.



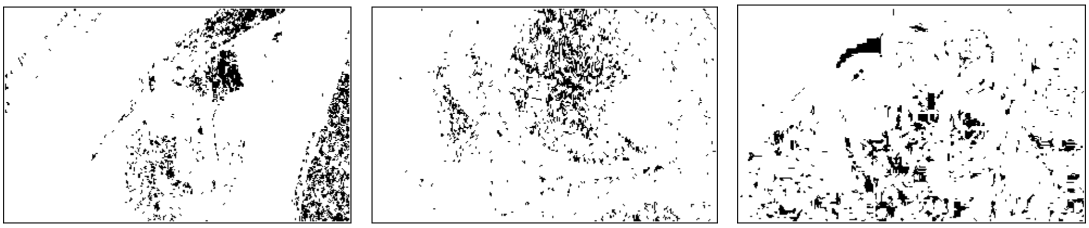


Fig. 6. G-sp image decomposition. First, second, fourth and tenth subimages are shown.

Pixel $p_{i,j;u}$ has coordinates i,j in the image space and position u in the grade ordered data table. Pixel is attached to some region R_w if it fulfils conditions:

pixel $p_{i,j;u}$ does not belong to any other existing region R_z,

pixel $p_{i,j;u}$ is distant in the grade ordered data table no more than a constant value g from any other pixel of region R_w,

pixel $p_{i,j;u}$ belongs to 8-neighborhood of any other pixel of region R_w.

Grade-spatial procedure joins pixels into regions. Procedure starts at the top of the grade ordered data table and attaches fitting pixels to existing regions or initializes new regions. Regions are disjoint sets of pixels. There are pixels which do not fulfil conditions, e.g. such pixels are more distant of pixels belonging to any region either in the image space or in the grade domain of the ordered data table. These pixels are regarded as single pixels which are not attached for a time. However, such pixels could be interesting from the grade analysis point of view as they are outliers.

Figure 6 presents some of subimages obtained with grade-spatial procedure. Regions are displayed in order of appearance in the data table. This assures greater similarity of pixels and regions shown in every subimage.

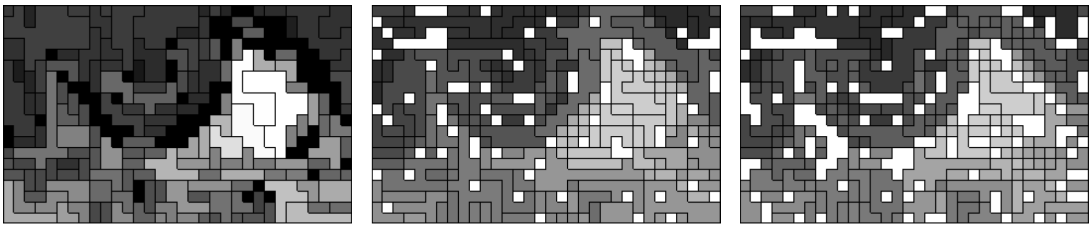


Fig. 7. Fragment of Lena image from Figure 1 – right eye; simple region growing procedure (left), grade decomposition (middle) and g-sp decomposition (right); regions are displayed with average gray level of region; white spots marks single pixels.

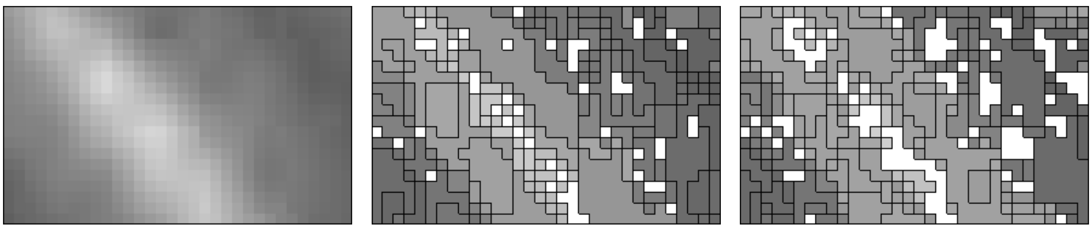


Fig. 8. Fragment of brain image from Figure 1 (left), grade decomposition (middle), g-sp decomposition (right).

Figure 7 presents fragment of Lena image, namely her right eye. The right image shows result of simple split and merge method for comparison purpose only. In the middle example of the grade decomposition is shown (10 cl. case), left is new grade-spatial example. There are more white spots of single pixels which is consistent with Figure 3. Shapes of an iris and an eye-lid are formed more precise. Figure 8 left shows fragment of the NMR brain image marked with black rectangle in Figure 1. In the middle is shown result of the grade decomposition, right is grade-spatial partition. The latest more precisely reflects non-uniform beads-shaped diagonal structure. In both figures regions are displayed in average gray level obtained across all pixels attached to region. Differences in shade can appear due to reducing float number to integer value or due to grouping pixels according another rule than gray level proximity, e.g. similar pixels belong to region but their gray levels may be not close.

4. RESULTS

The influence of clusters number on grade decomposition is inquired. Conclusion is drawn that increasing of the clusters number does not effect image decomposition improving. Increasing of number of clusters causes reduction of pixels gathered into regions. At the same time average size of regions considerably lowers.

Grade-spatial procedure inserts less pixels in regions than grade decomposition into ten clusters which can be seen in Figure 3 item g-sp and in Figures 7 and 8. Left images contain more white spots marking isolated pixels. Decreasing pixels number is considerable. Number of regions increases less (as is shown in Figure 4) and the average size of region lowers in admissible way. G-sp image decomposition is more exact than grade decomposition.

Constant value *g* which restricts range for candidate search in g-sp procedure is relative small. For image of size 320×200 constant *g* is near 3% of set size. Procedure is not sensitive to this parameter and the results are very similar if constant is diminished to half of this value. Single pixels require further consideration. Future progress is connected with linking regions into bigger meaningful structures. One of possible research is to apply extensive description of regions and to continue grade analysis to such description. However, application of average gray level and average gradient magnitude of region is too simple. Promising seems adapting mean-shift method [2] or normalized graph cuts [8] to obtained regions which methods are versatile and flexible. Application to medical images, in particular to NMR images will be developed.

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