IMAGE COMPRESSION TECHNIQUE BY REVERSIBLE CLUSTERING SEGMENTATION

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Abstract

For reducing the size of data in digital images, data compression algorithms are used in which minimize data that stored in digital form. As a result of compression, the size of imaged is reduced. In image coding, segmentation - is the process of separating the digital image into multiple segments (set of pixels). The purpose of segmentation is to simplify and / or change the representation of the image to make it simpler and easier to analyze or compress [1]. Image compression use data compression algorithms for images stored in digital form. As a result of compression reduces the size of the image, thus reducing the time for image transmission over the network and saves storage space [8]. In order to eliminate errors in image segmentation for image compression, a new method are proposed - (Reversible Cluster Progressive Segmentation) RCPS in which based on reverse clustering. The method consists of the selection of homogeneous brightness pixel regions with a compact description of image structure based on cluster of three types of cards, presented in the form of trees: Clustering Homogeneous, approximation and segmentation. Cluster maps are multilevel contain at each level of the multi-resolution representation of the image and processed reverse - first a map clustering and approximation (straight through), and then use them to map generated segmentation (back through). The method provides error recovery segmentation of structurally complex areas (texture images) by using a compact description to verify procedures adjacent segments at each level of clustering.

Keywords. Classic Quadra-Tree Segmentation CQTS, Modification Quadra-Tree Segmentation MQTS, Reversible Cluster Progressive Segmentation RCPS.

The method includes the initialization and two cycles - the allocation of areas based on iterative clustering (straight through) and advanced segmentation based on the division, merge and acquisition areas (back passage), as shown in the following sections.

1. FORMING A SET $\{A(l)\}_{(l=\overline{0,L})}$ OF MATRICES

$A(l)=\left\|a^{(l)}(y,x)\right\|_{\left(y=\overline{0,Y/2^l-1},\,x=\overline{0,X/2^l-1}\right)}$ Approximate and initialize the elements of $A(0)$ approximation of 0-level implemented in accordance with the expression

$$a^{(0)}(y,x)=p(y,x) \tag{1}$$

At $y=\overline{0,Y-1}$, $x=\overline{0,X-1}$,

Where $p(y,x)$ – pixels of image to be segmented $P=\left\|p(y,x)\right\|_{\left(y=\overline{0,Y-1},\,x=\overline{0,X-1}\right)}$; $Y=2^{f_Y}$, $X=2^{f_X}$ – size of image to be segmented P;

$f_Y>0$, $f_X>0$ – whole image;

$l=\overline{0,L}$ – Number of iteration of segmentation level;

$L=\min(f_Y,f_X)$ –number of iterations of the values determined by the minimum f_Y and f_X.

The output of this step as a way of approximated $A(0)$ is used the image to be segmented P.

2. CREATING SET $\{C(l)\}_{(l=\overline{0,L})}$ OF MATRICES

By creating set of matrices $C(l)=\left\|c^{(l)}(y,x)\right\|_{\left(y=\overline{0,Y/2^l-1},\,x=\overline{0,X/2^l-1}\right)}$

Approximation and initialize the elements of $C(0)$ approximation of 0-level implemented in accordance with the expression

$$c^{(0)}(y,x)=0 \tag{2}$$

At $y=\overline{0,Y-1}$, $x=\overline{0,X-1}$.

As a result of this step $C(0)$ clustering of zero level is initialized with zero.

3. CREATING SET $\{S(l)\}_{(l=\overline{0,L})}$ MATRICES

By creating set of matrices $S(l)=\left\|s^{(l)}(y,x)\right\|_{\left(y=\overline{0,Y/2^l-1},\,x=\overline{0,X/2^l-1}\right)}$ segmentation an initialization of segmented elements $S(l)$ segmentation level $\overline{0,L}$ carried out in accordance with expression

$$s^{(l)}(y,x)=0 \tag{3}$$

At $\overline{l=0,L}$, $y=\overline{0,Y-1}$, $x=\overline{0,X-1}$.

The output of this step is the matrix $S(l)$ segmentation of level $\overline{0,L}$ are defined as zeros.

4. THRESHOLDS

Choose different values of threshold sensitivity T_S to the different values of cluster elements, to make approximation, which are chosen from the range

$$0<T_S<1. \tag{4}$$

5. INITIALIZATION

Counter initialization of l cycles according to the expression

$$l=1. \tag{5}$$

6. CLUSTER FORMATION (STRAIGHT THROUGH).

Ongoing formation matrix $C(l)$ cluster of *l*-th level, its elements are calculated with the expression

$$c^{(l)}(y,x)=\begin{cases}0 \;\; at\;(S_C=0)\wedge(D_A\le T_S),\\ 1 \;\; at\;(S_C>0)\vee(D_A>T_S)\end{cases} \tag{6}$$

at $y=\overline{0,Y/2^l-1}$, $x=\overline{0,X/2^l-1}$,

where $S_C=\sum_{j=0}^{1}\sum_{i=0}^{1}c^{(l-1)}(2y+j,2x+i)$ – sum of the elements of cluster coordinate $(2y,2x)$ in matrix $C(l-1)$ cluster of lower $(l-1)$-th level; $D_A=\dfrac{\left(\max\limits_{j=0}^{1}\left(\max\limits_{i=0}^{1}\left(a^{(l-1)}(2y+j,2x+i)\right)\right)-\min\limits_{j=0}^{1}\left(\min\limits_{i=0}^{1}\left(a^{(l-1)}(2y+j,2x+i)\right)\right)\right)}{\max\limits_{j=0}^{1}\left(\max\limits_{i=0}^{1}\left(a^{(l-1)}(2y+j,2x+i)\right)\right)}$ – weighted difference between the maximum and minimum values of the cluster members with coordinates $(2y,2x)$ in matrix $A(l-1)$ approximation of lower $(l-1)$-th level.

The result of this step will gave a zero cluster $\left\{c^{(l-1)}(2y+j,2x+i)\right\}_{(j=\overline{0,1},\,i=\overline{0,1})}$ matrices $C(l-1)$ clustered $(l-1)$-th level and their corresponding values for homogeneous clusters

$\{a^{(l-1)}(2y+j,2x+i)\}_{(j=\overline{0,1},\,i=\overline{0,1})}$ Matrices $A(l-1)$ approximation of $(l-1)$-th level are assigned to the zero elements $c^{(l)}(y,x)$ matrices $C(l)$ cauterized the upper l-th level. The non-zero cluster $\{c^{(l-1)}(2y+j,2x+i)\}_{(j=\overline{0,1},\,i=\overline{0,1})}$ matrices $C(l-1)$, a also the zero cluster $\{c^{(l-1)}(2y+j,2x+i)\}_{(j=\overline{0,1},\,i=\overline{0,1})}$ matrices $C(l-1)$, having non uniform values corresponding clusters $\{a^{(l-1)}(2y+j,2x+i)\}_{(j=\overline{0,1},\,i=\overline{0,1})}$ matrices $A(l-1)$ approximation, are assigned to individual elements $c^{(l)}(y,x)$ matrices $C(l)$. Generate in this way for the L cycle -L leveled zero-trees describe the location of the cluster of homogeneous regions in a variety of $\{A(l)\}_{(l=\overline{0,L})}$ matrices $A(l)$ approximation $(l=\overline{0,L})$.

7. FORMATION MATRIX $A(l)$

Ongoing formation matrix $A(l)$ approximation l-th level, elements of which are calculated using the expression

$$a^{(l)}(y,x)=\begin{cases}0 \;\; at\; c^{(l)}(y,x)=1,\\ S_A \;\; at\; c^{(l)}(y,x)=0\end{cases} \tag{7}$$

at $y=\overline{0,Y/2^l-1}$, $x=\overline{0,X/2^l-1}$,

Where $S_A=\frac{1}{4}\sum_{j=0}^{1}\sum_{i=0}^{1}a^{(l-1)}(2y+j,2x+i)$ – the sum of cluster elements at the coordinates $(2y,2x)$ in matrix $A(l-1)$ approximation $l-1$ level.

The output of this step, the image is formed approximated level of image to be segmented as the following.

a) Increment cycle counter according to the expression

$$l=l+1. \tag{8}$$

Ending the cycle of clustering. The verification of the conditions

$$l\le L. \tag{9}$$

If (9) holds, the transition to the beginning of the loop clustering (step 6).

b) Initialize counter N_S segments according to the expression

.
$$N_S=0 \tag{10}$$

c) Initializing matrix $S(L)=\left\|s^{(L)}(y,x)\right\|_{(y=0,\,x=0)}$ segmentation L-th level, the value of the single element (top of the tree segmentation) is calculated using the expression

$$\left(c^{(L)}(y,x)=0\right)\rightarrow\left(\left(s^{(L)}(y,x)=1\right)\wedge\left(N_S=N_S+1\right)\right) \tag{11}$$

at $y=0$, $x=0$.

From the expressions (3), (6) and (11) that for a homogeneous images $s^{(L)}(0,0)=1$ (all images - one segment), and for non-uniform $s^{(L)}(0,0)=0$ (image consists of two or more segments).

d) Initialize loop counter *l* according to the expression

$$l=L. \tag{12}$$

e) Ongoing formation values of the elements of the matrix $S(l-1)$ of $(l-1)$ level segmentation by means of (scaling regions)

$$\left(c^{(l)}(y,x)=0\right)\rightarrow \forall j\left(j=\overline{0,1}\right)\forall i\left(i=\overline{0,1}\right)\left(s^{(l-1)}(2y+j,2x+i)=s^{(l)}(y,x)\right) \tag{13}$$

At $y=\overline{0,Y/2^{l}-1}$, $x=\overline{0,X/2^{l}-1}$.

The output of this step is formed –th level zero for cluster-trees.

f) Development of new areas (the separation of areas) according to the expression

$$\begin{gathered}\left(c^{(l)}(y,x)=1\right)\rightarrow\\ \rightarrow \forall j\left(j=\overline{0,1}\right)\forall i\left(i=\overline{0,1}\right)\Big[\Big[\left(c^{(l-1)}(2y+j,2x+i)=0\right)\wedge\\ \wedge\neg\exists k\left(k=\{-1,1\}\right)\neg\exists l\left(l=\{-1,1\}\right)\left(\begin{array}{l}\left(c^{(l-1)}(2y+j+k,2x+i+l)=0\right)\wedge\left(s^{(l-1)}(2y+j+k,2x+i+l)\neq 0\right)\\ \wedge\left(T_S\geq\dfrac{\left|a^{(l-1)}(2y+j,2x+i)-a^{(l-1)}(2y+j+k,2x+i+l)\right|}{\max\left(a^{(l-1)}(2y+j,2x+i),a^{(l-1)}(2y+j+k,2x+i+l)\right)}\right)\end{array}\right)\Big]\rightarrow\\ \rightarrow\left(\left(N_S=N_S+1\right)\wedge\left(s^{(l-1)}(2y+j,2x+i)=N_S\right)\right)\Big]\end{gathered} \tag{14}$$

At $y=\overline{0,Y/2^{l}-1}$, $x=\overline{0,X/2^{l}-1}$, $0\leq(2y+j+k)<Y/2^{l-1}$, $0\leq(2x+i+m)<Y/2^{l-1}$.

g) Initialize the matrix $B=\left\|b(j,i)\right\|_{\left(j=\overline{0,N_S},i=\overline{0,N_S}\right)}$ merging regions according to the expression

$$b(j,i)=0 \tag{15}$$

At $j=\overline{0,N_S}$, $i=\overline{0,N_S}$.

h) Merging areas by adding them to the existing homogeneous areas

$$\begin{gathered}\left(c^{(l)}(y,x)=1\right)\rightarrow\\ \rightarrow \forall j\left(j=\overline{0,1}\right)\forall i\left(i=\overline{0,1}\right)\Big[\Big[\left(c^{(l-1)}(2y+j,2x+i)=0\right)\wedge\\ \wedge\exists k\left(k=\{-1,1\}\right)\exists l\left(l=\{-1,1\}\right)\left(\begin{array}{l}\left(c^{(l-1)}(2y+j+k,2x+i+l)=0\right)\wedge\left(s^{(l-1)}(2y+j+k,2x+i+l)\neq 0\right)\\ \wedge\left(T_S\geq\dfrac{\left|a^{(l-1)}(2y+j,2x+i)-a^{(l-1)}(2y+j+k,2x+i+l)\right|}{\max\left(a^{(l-1)}(2y+j,2x+i),a^{(l-1)}(2y+j+k,2x+i+l)\right)}\right)\end{array}\right)\Big]\rightarrow\\ \rightarrow\left(\begin{array}{l}\left(b\left(s^{(l-1)}(2y+j,2x+i),s^{(l-1)}(2y+j+k,2x+i+l)\right)=1\right)\wedge\\ \wedge\left(b\left(s^{(l-1)}(2y+j+k,2x+i+l),s^{(l-1)}(2y+j,2x+i)\right)=1\right)\wedge\\ \wedge\left(s^{(l-1)}(2y+j,2x+i)=s^{(l-1)}(2y+j+k,2x+i+l)\right)\end{array}\right)\Big]\end{gathered} \tag{16}$$

at $y=\overline{0,Y/2^{l}-1}$, $x=\overline{0,X/2^{l}-1}$, $0\leq(2y+j+k)<Y/2^{l-1}$, $0\leq(2x+i+m)<Y/2^{l-1}$.

i) Formation of a vector $R=\left\|r(i)\right\|_{\left(i=\overline{0,N_S}\right)}$ change rooms segments whose elements are initialized with the expression

$$r(i)=0 \tag{17}$$

at $i=\overline{0,N_S}$.

j) Formation of a stack $Q=\|q(i)\|_{\left(i=\overline{0,N_S-1}\right)}$ of conflicting numbers of adjacent segments and initialize the stack pointer according to the expression

$$N_Q=0 \tag{18}$$

at $i=\overline{0,N_S{}^2}$.

k) processing stack conflicting numbers of adjacent segments

$$\begin{cases}(r(i)=0)\to\begin{pmatrix}(r(i)=i)\wedge \\ \wedge\left(\forall j\left(j=\overline{1,N_S}\right)(b(j,i)=1)\wedge((r(j)=0))\to((q(N_Q)=j)\wedge(N_Q=N_Q+1))\right)\end{pmatrix}, \\ (N_Q>0)\to\begin{pmatrix}(N_Q=N_Q-1)\wedge(k=q(N_Q))\wedge(r(k)=i)\wedge \\ \left(\forall j\left(j=\overline{1,N_S}\right)(b(j,k)=1)\wedge((r(j)=0))\to((q(N_Q)=j)\wedge(N_Q=N_Q+1))\right)\end{pmatrix}\end{cases} \tag{19}$$

at $i=\overline{1,N_S}$.

l) Changing numbers of segments in accordance with the expression

$$s^{(l-1)}(y,x)=r\left(s^{(l-1)}(y,x)\right) \tag{20}$$

at $y=\overline{0,Y/2^{l-1}-1}$, $x=\overline{0,X/2^{l-1}-1}$.

m) Reduce the cycle counter according to the expression

$$l=l-1. \tag{21}$$

n) The end of the cycle of progressive segmentation.
Then verificate of the conditions

$$l>0. \tag{22}$$

If (22) holds, the transition to the beginning of the cycle of progressive segmentation (step 13-e).

8. RESULTS

The proposed method RCPS progressive image segmentation based on reverse clustering provides accurate localization of any complexity. The closest to it on the principles of organization and functioning of the method are CQTS split and merge regions based on the square of the tree [1,2,3,4,5,6,7] and its modification MQTS [8]. As an example, Figure 1 shows the results of the segmentation of complex images obtained by the methods of RCPS, CQTS and MQTS among MATLAB (used software-based methods and CQTS and MQTS, members of the library of MATLAB). As follows from Figure 1, the segmentation results obtained using the proposed method RCPS, without error in contrast to the results obtained with CQTS and MQTS. To assess the effectiveness of the method in the natural lighting conditions, by using a collection of test grayscale images shown as shown in table 1. Performed segmentation of image data using the proposed method and the method of RCPS and MQTS [8].

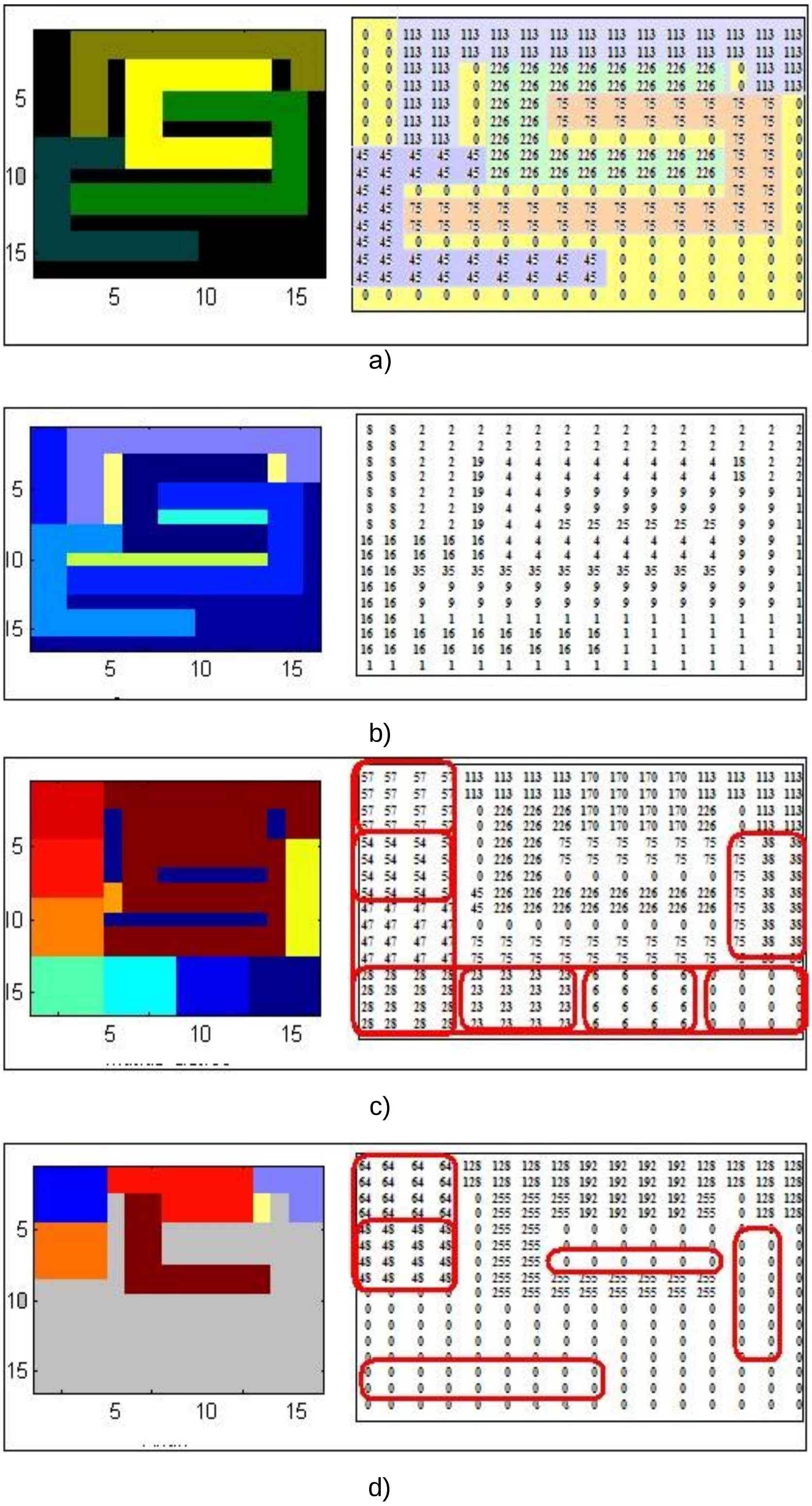

Figure 1 - Segmentation: the test pattern (s), the results for the method of RCPS (b) for the method CQTS (a) for the method MQTS (d)

To assess the effectiveness of the methods used sustainability performance of segmentation results to change the brightness ($S_Y(N_S)$) and contrast ($S_C(N_S)$) image calculated using expressions

$$S_Y(N_S) = \frac{\Delta N_S(\Delta Y)}{\Delta Y}, \tag{23}$$

$$S_C(N_S) = \frac{\Delta N_S(\Delta C)}{\Delta C}, \tag{24}$$

Where $\Delta Y = Y_{MAX} - Y_{MIN}$ и $\Delta C = C_{MAX} - C_{MIN}$ – intervals of brightness and contrast, which is the stability analysis of segmentation results; Y_{MAX}, Y_{MIN} – The maximum and minimum values that define the intervals of stability analysis of segmentation results to a change in brightness; C_{MAX}, C_{MIN} – The maximum and minimum values of contrast, determining the intervals of stability analysis of segmentation results to a change of contrast; $\Delta N_S(\Delta Y) = N_{S\,MAX}(\Delta Y) - N_{S\,MIN}(\Delta Y)$ A range of changes in the number N_S of segments on the interval ΔY ; $\Delta N_S(\Delta C) = N_{SMAX}(\Delta C) - N_{SMIN}(\Delta C)$ – the range of segments number N_S at interval ΔC

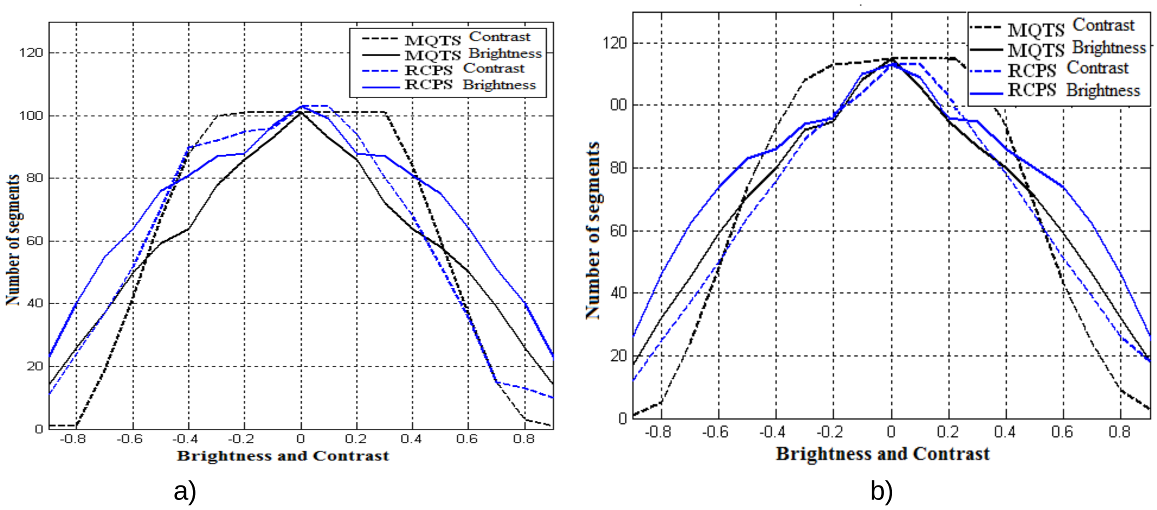

Figure 2 - The dependence of the number of segments on the brightness and contrast of images: Barbara (a); Lena (b);

Gray scale images	Threshold sensitivity number	
	RCPS method	MQTS method
Barbara	0.273	0.790
Lena	0.239	0.751
Home	0.140	0.725
Cameraman	0.200	0.880
Peppers	0.160	0.825
Couple	0.180	0.860
Hill	0.150	0.644
Simple	0.260	0.470

Table 1 - Values of the sensitivity in the methods RCPS and MQTS

Fig. 2 shows that the proposed method RCPS more resistant to changes in brightness and is more sensitive to changes in contrast to the method MQTS (for most images RCPS stability of the method is increased by 5 - 20% compared to MQTS). This is due to the exception in the method of RCPS segmentation errors and to improve the stability and quality of segmentation.

9. CONCLUSION

A method of image segmentation based on reversible clustering, eliminates the segmentation fault in structurally complex areas by using of a compact description of verification procedures adjacent segments at each level of clustering. It's found that the increase in the accuracy of segmentation will add a positive effect on the stability of the results by changing brightness and sensitivity to changes in contrast. It is shown that the stability of segmentation results for most classes of images increases by 5 - 20% with respect to the methods that depends on split and merges areas.

REFERENCES

[1]. Rafael C. Gonzalez, Digital image processing, 793 p , Publisher: Prentice Hall; 2nd edition, January, 2002.

[2]. Optimization Based Image Segmentation by Genetic Algorithms / S. Chabrier [et al.]. // The European Association for Signal Processing (EURASIP), Journal on Video and Image processing. 2008. – Vol. 2. – P. 1–23.

[3]. Ching, Y. Detecting K-Line Segments in an Image New Implementation for hough transform / Y. Ching // International Computer Symposium Workshop on Image Processing and Charichter Recognition, N. C. K. U., Tainan, Taiwan, R.O.C., 17–19 December 1998. – 1998. – P. 144–151.

[4]. Image processing; analysis and machine vision / Milan S. [et al.]. Thomson press, West, 2008. – P. 175-240.

[5]. Ritter, X.G. Handbook of Computer Vision Algorithms in Image Algebra / X.G. Ritter, J.N. Wilson // Center for Computer Vision and Visualization, University of Florida CRC Press LLC. – 1996. – 425 p.

[6]. Wang, J. An iterative optimization approach for unified image segmentation and matting Journal: Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1,Year: 2005 Vole: 2 Pages: 936-943Vol.2: 10.1109/ICCV.2005. (IVSL)

[7]. Yu-Jin, Z. Advanced in image and video segmentation / Z. Yu-Jin. // USA, IRM press, 2006. – 457 p.

[8]. Khan, M. A Hybrid Image Compression Technique using Quadtree Decomposition and Parametric Line Fitting for Synthetic Images / M. Khan, Y. Ohno // Advances in Computer Science and Engineering conference, Publishing house, Allahabad, India. – 2007. – Vol. 1, № 3 -P. 263–283.