Conceptual Basis of Cascading Differential Masking Technology

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Abstract – **the analysis of image processing technologies shows the main practice way to improve the quality of image processing. It is a preliminary analysis and subsequent image processing. It depends on the result of the preliminary analysis (filtering, sharpening, noise reduction, etc.). However, when selection of the method of preliminary analysis, an intermediate evaluation of results, selection of the subsequent processing method, etc. decision makers involved. This is not acceptable for practical implementation in automatic processing and transmission of video information systems.**

Keywords – image, technologies, method, filtering, videoinformation systems, detection, localization, indicator, semantic saturation.

I. INTRODUCTION

To solve the scientifically-practical problem, it is proposed to perform following stages of differential video images processing with the introduction of intellectual analysis, namely:

a) a detection and localization of semantically significant information in video images;

b) a performing fragmented analysis of video images with classification of semantic complexity (degree of saturation by contours);

c) an implementation of a compact representation of video images, the parameters of which will be adaptively determined depending on the class of semantic complexity.

It is proposed to perform 2-cascade differential processing of video images for the following tasks:

a) increasing the number of correctly allocated boundary pixels (high detection level);

b) increasing the localization degree of contours with synchronous fragments classification of images by the degree of contours saturation;

c) providing an information for managing image compression parameters.

The use of 2-cascade differential video images processing in video conferencing systems [1-3] will eliminate the shortcomings of existing masking technologies with the continuity of video information.

Cascading video processing will consist of:

a) preliminary analysis of image fragments in terms of saturation by their contours (weak, medium and highly saturated);

b) the use of various masking methods for cascades of different levels of the contour selection scheme, taking into account the saturation class of the fragments.

In the first cascade of the circuit, the following problems are solved in [4-6]:

a) the contours are selected in the image using masks of the 1st level (false contours can be selected);

b) the estimation of the indicators of the structural complexity of the image (fragments) is performed.

The second cascade is realized [7-8]:

a) classification of images (fragments) in terms of saturation by their contours;

b) localization of the contours of image objects by a mask of the 2nd level, taking into account the saturation class of the contours;

c) definition of the compression method parameters for the video image (fragmented) depending on the saturation class of the contours.

II. A CASCADE IMAGE PROCESSING SCHEME WITH ANALYSIS OF THE FRAGMENT CLASS

A cascade image processing scheme with analysis of the fragment class is proposed as follows.

In the **first** stage, it is proposed to use primary (coarse) masking of image fragments to reduce the processing time and to extract semantic information. For these purposes, it is necessary to use a method that ensures that real contours are not skipped. It uses the minimum (maximum) error value of the second kind (sensitivity)). The purposes of this processing stage are:

a) determination of structural indicators of image saturation (the number of binary differences, the length of binary series, etc.); b) automatic classification of image areas according to the degree of saturation (filling density) of their contours.

The steps of selecting and localizing contours in the original image X by masking methods and the result of masking will be denoted by M (X).

For the first cascade it is suggested to use the Sobel or Laplacian methods (LoG), for the second cascade – the Sobel, Laplace or Sharou methods.

To identify the semantics of images using the proposed cascade approach, it is necessary to determine the structural complexity indicators of the image in the first scheme's cascade. They will allow us to classify fragments of images according to the degree of their semantic saturation by contours.

III. The structural complexity indicators of the image for the classification of masked images by the degree of their semantic saturation

As a result of the studies [9], the following parameters of the structural images' complexity (absolute and relative values) were proposed for estimating the saturation of the image contours (fragments):

1) parameter P_1 – the number of columns N_{col} of the video image (fragment);

2) parameter P_2 – the number of rows N_{row} of the video image (fragment);

3) parameter P_3 – the averaged value of binary differences in the rows relative to the columns:

$$P_3 = n_1' = \frac{\sum_{x=1}^{Ncol} n_{1x}}{N_{row}} \qquad (1)$$

where n_{1x} is the number of binary differences in the x-th line;

N_{col} – the number of columns;

N_{row} – the number of rows;

x is the sequence number of the row;

4) parameter P_4 – the average value of the binary differences in the columns relative to the rows:

$$P_4 = n_2' = \frac{\sum_{y=1}^{N_{col}} n_{2y}}{N_{row}}, \qquad (2)$$

where n_{2y} is the number of binary differences in the y-th column;

Y is the sequence number of the column;

5) a parameter P_5 – the integral parameter of the number of binary differences:

$$P_5 = n = \sqrt{n_1'^2 + n_2'^2}; \qquad (3)$$

6) a parameter P_6 – the total number of pixels in the contours – $N_{pix\,cont}$;

7) a parameter P_7 – the integral parameter of specific saturation by contours – the ratio between the contours area S_{cont} to the image area S_{im} (in %):

$$P_7 = \Delta S = \frac{S_{cont}}{S_{im}} \cong \frac{N_{pix\,cont}}{\mathrm{N}_{pix\,im}}, \qquad (4)$$

where $N_{pix\,cont}$ is the total number of pixels in the contours;

$\mathrm{N}_{pix\,im}$ – the total number of pixels in the image;

8) a parameter P_8, the class of semantic saturation by contours (CSC):

1 – weakly saturated, 2 – medium unsaturated, 3 – strongly saturated.

The proposed parameters of the structural image complexity are calculated at the output of the 1st stage at the processing scheme.

The estimates set P of the structural complexity indicators for the original image X is represented as follows:

$$P = F_{\mathrm{P}}(X;\, M) = \{P_j\},\ j = \overline{1, n_p}, \qquad (5)$$

where $F_P(X; M)$ is the system of determining the structural parameters P_j for the original image X based on the masking results M;

P_j – j-th index of estimation of structural complexity for image X;

n_p – the number of indicators considered.

Structural measures of complexity P in general case depend on the parameters of the original image X (its semantic structure), and on the result of masking - M (X). The structural indicators analysis and processing of complexity allow us to determine the class of images (fragments) semantic saturation.

In the **second** stage, based on the obtained values, the class of semantic saturation of the image fragment is determined. For fragments highly saturated with contours, secondary (clarifying) masking is carried out by methods that ensure:

– a high degree of localization;

– no rupture in the contours;

– unbiased boundary pixels;

– the minimum (maximum) value of the error of the first kind (specificity) and the minimum value of RMSE.

The results of the experiments are summarized in the results tables according to the following standard form:

a) № – the conditional number of the processed realistic image (fragment);

b) the values (samples) of the computed structural parameters (conditional parameters P_1–P_7 and the corresponding real parameter). For example, P_1 is the average value of binary differentials in rows relative to columns, etc.;

c) quality attribute P_8. It is determined on the basis of the cluster analysis of the parameters P_1–P_7.

Processing of experimental results for a large number of images allows us to form ranges of indicators values of the structural complexity of the image for each class of saturation by contours.

Moreover, the entire estimates' set P of the structural complexity indicators for the images processed as a result of the research is empirically divided into P_i realizations subsets P_i.

P_i are subsets of the implementations of indicator valuesfor each class of semantic saturation:

$$P = \{P_i\}, \tag{6}$$

where P_i is the corresponding subset of the estimates of the structural complexity indicators for the i-th saturation class of the image (or its fragment);

i – is the sequence number of the saturation class, $i = \overline{1, m_S}$;

m_S – the number of saturation classes.

The clusters formation (subsets) P_i of estimates of structural complexity indicators for the i-th class of image (fragment) saturation is proposed to be carried out by cluster analysis methods. Such methods are the hierarchical agglomeration method, the K-medium method or fuzzy clustering methods, for example, the fuzzy C-medium method. The formation of clusters is carried out according to the obtained experimental estimates of structural complexity indicators when processing video images of real videoconferencing sessions [10-11].

Depending on the degree of saturation of the contours, it is suggested to consider 3 classes of saturation of images by contours (CSC):

weakly saturated by contours – CSC "weakly saturated";

medium saturated by contours – CSC "medium-saturated";

strongly saturated by contours – CSC "strongly saturated".

To solve this problem, we introduce a gradation of classes of semantic saturation of images: with a class of semantic saturation "weakly saturated" – K_1; with the class of semantic saturation "medium-saturated" – K_2; with a class of semantic saturation "highly saturated" – K_3.

To classify images (fragments) according to the degree of their saturation by contours, the following approach is proposed. First, we find the values of structural complexity indicators ($P1$–$P7$). Let us determine the correspondence of the calculated indicators to a subset P_i of structural complexity indicators. This subset corresponds to a certain class of semantic complexity K_i:

"weakly saturated" images (fragments) – $\{K_1 | P_i \subseteq P_1\}$;

"medium-saturated" images (fragments) – $\{K_2 | P_i \subseteq P_2\}$;

"highly saturated" images (fragments) – $\{K_3 | P_i \subseteq P_3\}$.

Then the procedure for determining the class of semantic saturation for the image (fragment) can be functionally represented as follows:

$$K = F_K(X; M; P) = \begin{cases} K_1, if \quad P_i \in P_1; \\ K_2, if \quad P_i \in P_2; \\ K_3, if \quad P_i \in P_3, \end{cases} \tag{7}$$

where $F_K(X; M; P)$ is a functional description allowing to determine the saturation class for the original image X (its fragment) from the found values P_j. P_j – estimates of structural complexity indicators, provided that the entire set of realizations of the values of the structural complexity parameters is divided into 3 saturation classes. The original image X (its fragment) is masked (M) in accordance with $F_P(X; M)$;

P_1, P_2, P_3 – the clusters of estimates of structural complexity indicators corresponding to the K_i saturation class.

The experimental results for 20 different in size and video images saturation fragments of real sessions are presented in table 1.

Experts visually evaluated fragments of images by the degree of saturation of their contours. According to the results of this assessment, fragments are classified as follows:

a) CSC "weakly saturated" – images: C_1, C_4, C_9, C_11; b) CSC "medium-saturated" – images: C_3, C_5, C_6, C_7, C_8, C_10, C_16, C_17, C_19, C_20; c) CSC "strongly saturated" – images: C_2, C_12, C_13, C_14, C_15, C_18.

As a result of the evaluation of the structural parameters (Table 1) by the method of cluster analysis, the images are classified according to their saturation degree by their contours as follows:

a) CSC "weakly saturated" - images: C_1, C_4, C_9, C_11, C_16; b) CSC "medium-saturated" - images: C_3, C_5, C_6, C_7, C_10, C_17, C_19, C_20; c) CSC "highly saturated" - images: C_2, C_8, C_12, C_13, C_14, C_15, C_18.

A comparative evaluation of the research results shows [12-13] that the visual estimate of the semantic saturation degree and the quantitative estimate based on cluster analysis are the correspondence.

Table 1.

An example of estimating the parameters of the images' structural complexity

№	№ im	P1 N_{col}	P2 N_{row}	P3 n'_1	P4 n'_2	P5 n	P6 N_{pix}	P7 ΔS	P8 CSC
1	C_1	100	100	0,28	0,38	0,47	342	0,03	1
2	C_4	100	100	0,12	0,42	0,44	468	0,05	1
3	C_9	100	100	0,44	0,66	0,79	244	0,02	1
4	C_11	480	320	0,71	1,27	1,45	463	0,00	1
5	C_16	480	320	0,83	1,52	1,73	1348	0,01	1
6	C_3	100	100	0,64	0,56	0,85	1346	0,13	2
7	C_5	100	100	0,76	1,08	1,32	1502	0,15	2
8	C_6	100	100	1,82	1,94	2,66	1934	0,19	2
9	C_7	100	100	1,96	3,49	4,00	2346	0,23	2
10	C_10	100	100	1,08	1,56	1,90	408	0,04	2
11	C_17	480	320	1,41	2,80	3,13	3456	0,02	2
12	C_19	480	320	2,06	2,74	3,43	2468	0,02	2
13	C_20	480	320	1,27	2,26	2,59	2349	0,02	2
14	C_8	100	100	2,33	2,67	3,54	4016	0,40	3
15	C_2	100	100	3,72	3,42	5,05	3204	0,32	3
16	C_12	480	320	13,6	23,20	26,9	15607	0,10	3
17	C_13	480	320	7,17	6,40	9,61	9876	0,06	3
18	C_14	480	320	4,89	6,36	8,02	7643	0,05	3
19	C_15	480	320	2,50	5,14	5,72	6378	0,04	3
20	C_18	480	320	1,18	3,76	3,94	3248	0,02	3

This correspondence allows us to work out empirical recommendations regarding the automatic classification of the semantic complexity of video images without operator involvement. This will allow the adaptive definition of compression parameters in the developed image processing method with masking depending on the semantic saturation of the video images [14-15].

In general, the scheme of 2-cascade differential processing of video images is shown in Fig. 1

An example of the images classification according to the CSC in the STATISTICA software environment for the experimental results presented in Table 1 for the P_1–P_7 indicators by P_5 (n is the integral parameter for estimating the binary differences) is shown in Fig. 2.

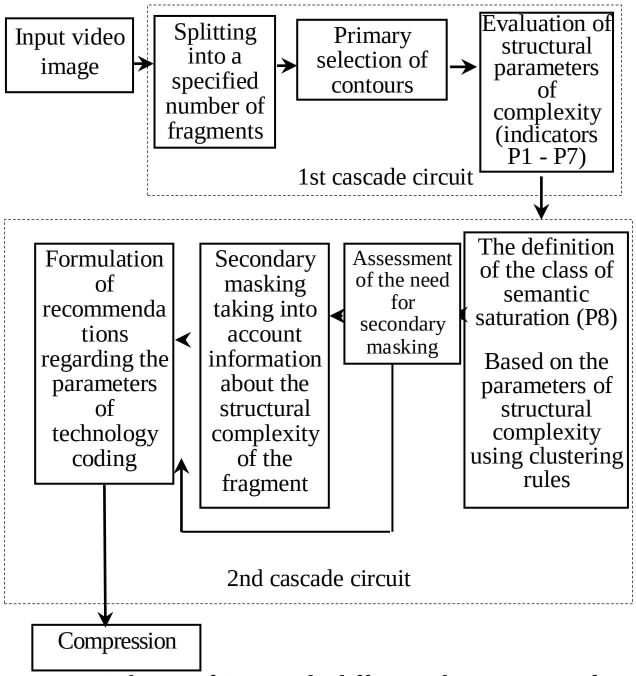

Fig. 1. Scheme of 2-cascade differential processing of video images

Analysis of the comparative evaluation of effectiveness showed us the following. The accuracy of isolating and localizing the semantic component (up to 30%) when masking video images is increased compared to simple masking methods. At the same time, the processing time for relatively simple masking methods increases by no more than 5%.

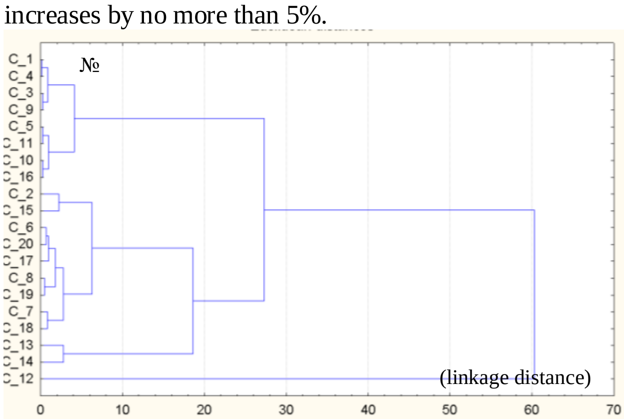

Fig. 2. Hierarchical classification (in the form of a dendrogram) of the experimental result (according to Table 1)

IV. Conclusion and Future Work

1. In the paper has been conducted a rule on the basis of the analytical expressions system for quantitative indicators of the image structural complexity.

processed image (the number of rows and columns); discontinuity of the brightness function (definition of binary differences); the two-dimensionality of the images' digital representation (the definition of binary differences in rows relative to columns and rows relative to columns); total number of pixels in the contours (the parameter of specific saturation by contours).

The developed indicators of the image structural complexity provide an estimate of the semantic saturation degree of the images and the subsequent classification of the video images (fragments) saturation by contours.

2. Cascading masking technology has been developed. It allows us to eliminate the disadvantages of separately used methods while maintaining the advantages of masking technology in general.

This technology is based on the following conceptual components: detection and localization of semantically significant information in video images using masking technologies; determination of the structural complexity indicators of the image for evaluating the characteristics of the image's (fragments) semantic saturation; classification of masked fragments according to the degree of semantic saturation based on cluster analysis; secondary masking to improve the accuracy of the selection and localization of semantics in the image for fragments with the class of semantic saturation "highly saturated".

3. Implementation of compact presentation of video images. Its parameters will be adaptively determined depending on the class of semantic complexity

4. A two-stage image masking technology has been created. It based on the using of filter masks and the definition of complexity structural indicators of video fragments. It allows us to increase the efficiency of contours detection, namely, the accuracy of the allocation and localization of the semantic component up to 30% with an insignificant increase in the total processing time (no more than 5%). The class of semantic complexity will be taken into account at the stage of video images code representation. This provides an increase in the availability and integrity of the video information resource in videoconferencing systems during crisis management.

5. In future work, we are planning to research:

- the method for determining the degree of video images semantic. A distinctive feature of the method will be based on the fact that quantitative structural indicators are applied on the basis of the estimation of the contour complexity of video images fragments. This will be ensures automatic classification of video images fragments in terms of the semantic saturation degree;

- the method of two-stage differential masking of video images will be developed. A distinctive feature of the method lies in the fact that the first stage of the scheme performs the determination of the indicators of the structural complexity of the video images fragments, and the classification of the image fragments semantic saturation is finally performed in the second cascade of the scheme. This will allow organizing adaptive processing in view of the semantic content of the video image and preserving the original semantic integrity.

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