BLOCK-BASED IMAGE EXPOSURE ASSESSMENT AND INDOOR/OUTDOOR CLASSIFICATION

S. Efimov, A. Nefyodov, M. Rychagov
Image Enhancement Technology Group,
Samsung Research Center, Moscow, Russia
sergei.efimov@samsung.com
michael.rychagov@samsung.com

Abstract

Automatic image quality assessment as well as image classification onto indoor/outdoor ones are performed by subdivision of image under analysis onto a number of fragments. Detecting overexposed, underexposed, low contrast or normal images is carried out by analyzing luminance histogram of the image and its constituting segments. At the stage of image classification, support vector machines (SVMs) are used for color features processing for each fragment of the image and wavelet analysis is used for texture description.

Keywords: *Image quality assessment, image classification, support vector machines*

1. INTRODUCTION

Several techniques can be found in digital image processing literature, manual as well as automated, to enhance visual perception of an image, in particular, to restore an optimum brightness and contrast.

In most cases, when these techniques operate in an automatic mode, they require high-performance automatic image assessment and image analysis algorithms. Such algorithms could provide a decision on a need of the image correction and, if required, to determine what type of the correction is necessary and how strong this correction should be.

Although defects of digital images are apparent both on global and on local levels, most methods of image quality assessment operate with global image characteristics. The reason lies in the fact that obtaining local image statistics requires detection of visually important areas, i.e. regions of interest, so that the required enhancement can be performed in these regions. Automatic detection of regions of visual importance assumes effective solution of object or pattern recognition problems. Till now, this is an open problem for a broad class of applications in image processing.

In a simpler embodiment, to analyze an image locally, the image is first subdivided into a number of rectangular blocks (or segments) of approximately the same size. For example, in [1], the number of horizontal divisions is kept equal to the number of vertical divisions so that each of the resulting segments has the same aspect ratio as the original image.

In the first part of present paper, it is shown how similar segmentation-based approach can be utilized for image evaluation as underexposed, overexposed, low contrast or normal ones.

In the second part, it is demonstrated that similarly to the above mentioned exposure estimation case, it is reasonable to perform image classification, in particular into indoor-outdoor classes by computing image features not for the whole image, but for image sub-blocks. The features commonly used for that purpose are color and texture features. Color features are usually obtained from histograms of pixel intensities in each channel of RGB color space or in transformed one. Texture features include various properties of the co-occurrence matrix, entropy, and homogeneity over particular image regions, as well as Fourier, Haralik, and wavelet descriptors [2-5].

It is also found reasonable to classify each image block separately using single classifier and then combine these results in order to classify the whole image. Presently, correct classification rate about 90% may be achieved in indoor/outdoor classification by using hierarchical classification methods and color and texture features of the image [6].

In general, the results presented here show that in some cases, like exposure estimation or image classification, subdivision of large size images provides a more appropriate way for the problem solution than processing of entire image.

2. IMAGE QUALITY ASSESSMENT

The contrast of the image can be defined for large regions, i.e. the entire image (global contrast), or for small regions within the image (local contrast). High-contrast regions tend to have a strong visual significance. This is because high global contrast means better isolation of the object from the background. Also, high local contrast reveals details more clearly in sharp areas.

Figure 1 demonstrates the results of classification and corresponding image histograms having entire images as inputs [7].

The method for estimation of image quality in the present work utilizes a segmentation-based approach for image analysis and characterization, in particular, as underexposed, overexposed, low contrast or normal images [8].

Figure 2 represents an image subdivision in which entire images are subdivided into four and nine blocks. Such subdivision in image quality assessment procedure is similar to multi-scale image representation used in algorithms of image similarity matching or establishment of image regions of interest for adaptive exposure correction.

Blocking is a useful step in additional identification visually important regions within an image and more precise estimation of its quality from the point of view of exposure errors, if any. The block size is an important design parameter. If the block size is too large, intensity variation will be averaged on large area and the necessary accuracy in quality evaluation of important regions will not be achieved. If the size is too small, each block may contain a part of the image with uniform color, which will be classified as low contrast region. In practice, 2 x 2 to 4 x 4 blocking for large size images (like 5 MP and more) gives good results. Further subdivision does not lead to increase of the quality.

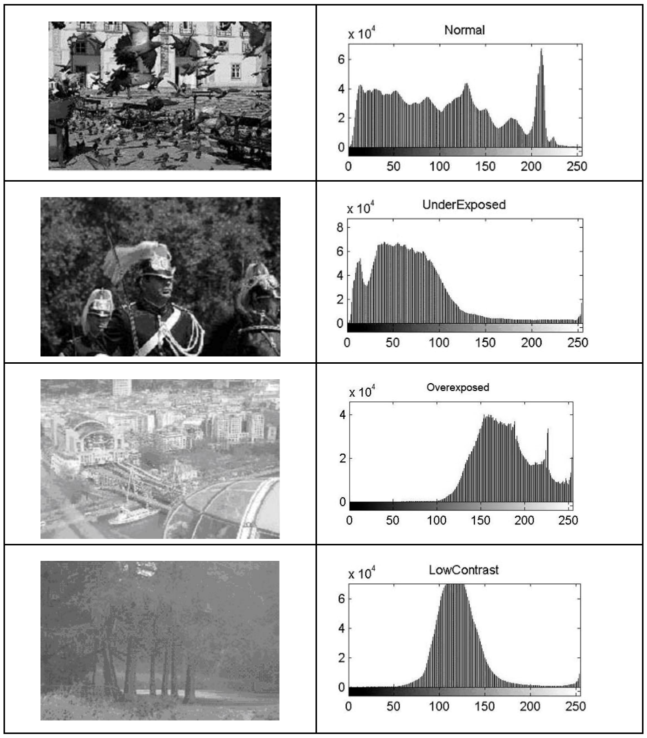

Figure 1: Results of classification and corresponding histograms

Figure 2: Image subdivision onto 2 x 2 and 3 x 3 regions

Figure 3 shows the results of classification of *Underexposed image* and its appropriate classification by 4 and 9 sub-regions. The histogram of initial image as well as a result of its classification are given on the right side. Shadowed (underexposed) areas are hatched horizontally, low-contrast areas are black, and highlighted (overexposed) areas are hatched vertically. The areas with correct exposure are white. It is demonstrated how an increase of the number of subdivision regions reveals more delicate structure of the image.

Figure 4 shows similar results for image quality assessment of the *Overexposed image*. An assessment of the image quality on the basis of parameter Normal can be obtained from Table 1.

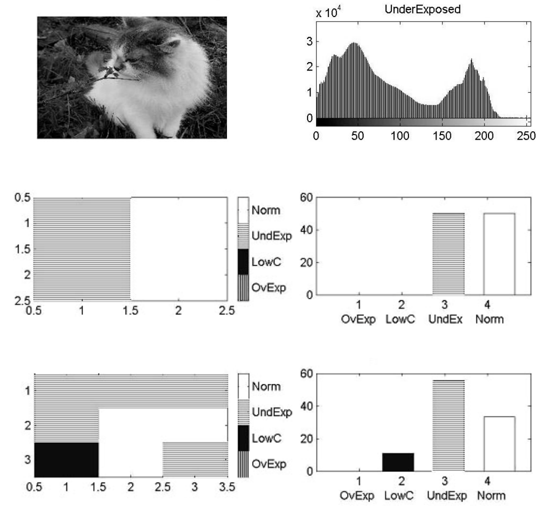

Figure 3: Results of global and local classification of *Underexposed image*

Table 1.

Parameter value Normal, %	Image quality
89 – 100	Excellent
78 – 88	Good
55 – 77	Satisfactory
Below 55	Bad

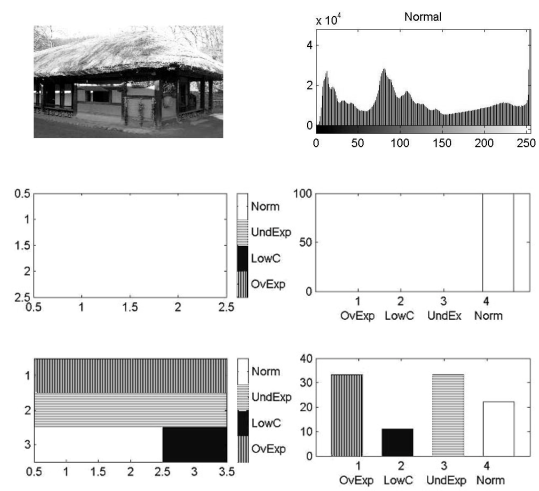

Figure 4: Results of global and local classification of *Overexposed image*

The parameter value is calculated from each particular quadrant. That is, in the first approximation, if for example just one part among 9 those of the image is estimated as normal, then the parameter value is approximated as 100/9 ~ 11, 2 image parts put together the parameter value ~ 22 and so on.

3. INDOOR/OUTDOOR IMAGE CLASSIFICATION

Let us convert the given image from RGB into LST color space using the following equations:

$$L = \frac{k}{\sqrt{3}}(R + G + B),$$

$$S = \frac{k}{\sqrt{2}}(R - B),$$

$$T = \frac{k}{\sqrt{6}}(R - 2G + B),$$

where *k = 255/max(R, G, B)*, and *max(R, G, B)* denotes the maximum value in red, green and blue channels of the image. This color space transformation is used to de-correlate color channels in the original RGB image. After that, the image is subdivided into fragments (Fig. 5), and both color and texture features are calculated for each fragment.

For texture description, a wavelet analysis is used; it provides texture description in terms of image frequencies at different spatial scales. The particular choice of wavelet filter is not critical for texture analysis. In our case, these features are obtained with the help of a two-level wavelet decomposition using Daubechies' filter [3].

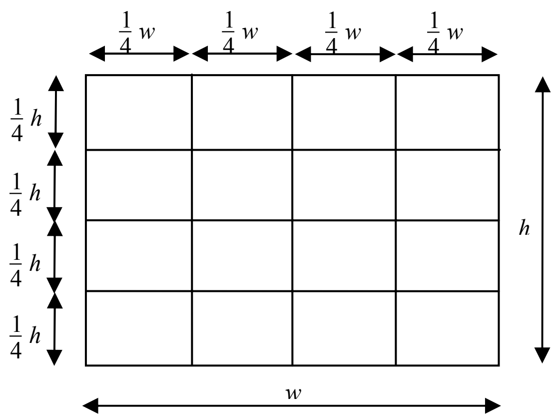

Figure 5: Image subdivision onto the fragments for indoor/outdoor classification

Texture features e1, e2, … , e8 are defined according to the standard equation:

$$e_k = \frac{1}{M_k N_k} \sum_{i=1}^{M_k} \sum_{j=1}^{N_k} c_k^2(i, j)$$

where k = 1, 2, … , 8, and $c_k(i, j)$ are sub-band coefficients of the two-level wavelet decomposition of the image fragment on a level *k*.

The low-pass filter *h(*)* and the high-pass filter *g(*)* are defined by using the optimized coefficients which are found during numerical modeling.

<u>1st level of decomposition</u>

Approximation coefficients	$c_1(i, j)$	$i = 1, 2, \dots, M_1$
		$j = 1, 2, \dots, N_1$
Horizontal detail coefficients	$c_2(i, j)$	$i = 1, 2, \dots, M_2$
		$j = 1, 2, \dots, N_2$
Vertical detail coefficients	$c_3(i, j)$	$i = 1, 2, \dots, M_3$
		$j = 1, 2, \dots, N_3$
Diagonal detail coefficients	$c_1(i, j)$	$i = 1, 2, \dots, M_4$
		$j = 1, 2, \dots, N_4$

<u>2nd level of decomposition</u>

Approximation coefficients	$c_5(i, j)$	$i = 1, 2, \dots, M_5$
		$j = 1, 2, \dots, N_5$
Horizontal detail coefficients	$c_6(i, j)$	$i = 1, 2, \dots, M_6$
		$j = 1, 2, \dots, N_6$
Vertical detail coefficients	$c_7(i, j)$	$i = 1, 2, \dots, M_7$
		$j = 1, 2, \dots, N_7$
Diagonal detail coefficients	$c_8(i, j)$	$i = 1, 2, \dots, M_8$
		$j = 1, 2, \dots, N_8$

For classifying current fragment into indoor or outdoor class using calculated features, support vector machine (SVM) is applied with the radial basis kernel function

$$K_1(u, v) = \exp(-\|u - v\|^2),$$

where || u – v || is a norm of vector u – v. Each of the fragments of the image is classified using individual SVM.

Final classifier is applied to the outputs of classifiers associated with the fragments in order to classify the whole image. For this classification, SVM with the polynomial kernel function $K_2(u, v)$ is used

$$K_2(u, v) = \left(\frac{1}{10}(u, v)\right)^3,$$

where *(u, v)* is a scalar product of vectors u, v.

The reported accuracy of modern methods for image classification into indoor-outdoor classes varies from 90 to 94% for different image bases. During testing, the proposed classification method gives classification accuracy of 92,5% on a test base of 1000 images.

The classification algorithm described in this section has been implemented in software utility. This utility is realized as a standalone application and as a component for commercial s/w package (Fig. 6).

Figure 6: Screenshot of s/w package with realized indoor/outdoor classification option

4. CONCLUSION

Image processing procedures, i.e. quality assessment, enhancement, classification, etc., usually treat images in a global manner, i.e. image in whole, while in many cases it is necessary to adapt image transformation to the local features in different regions of the image.

Image quality assessment technique described above is able to perform an image estimation both on global and local levels which becomes apparent in more precise performance of automatic procedure. For examples, incorrect image “enhancement” is eliminated when good digital images will be deteriorated due to the incorrect defection classification.

Correct selection of the subdivision is still not evident. In case of too large segments, the necessary accuracy in quality evaluation or classification can not be achieved. If the size of the fragment is too small, the informative capacity of the selected block will below for correct processing of the entire image.

5. REFERENCES

[1] S. Bhukhanwala, & T. Ramabadran, *Automated global enhancements of digitized photographs, IEEE Transactions on Consumer Electronics, 40(1), 1994, 272-278.*

[2] M. Szummer & R.W. Picard, *Indoor-outdoor image classification, Proc. of IEEE Int. Workshop on Content-Based Access of Image and Video Database, 1998, 42-51.*

[3] N. Serrano, A. Savakis, & J. Luo, *A computationally efficient approach to indoor/outdoor scene classification, Proc. Int. Conf. on Pattern Recognition, 2002, 146-149.*

[4] Le Lu, Kentaro Toyama, & G. D. Hager, *A Two Level Approach for Scene Recognition, IEEE Conference on Computer Vision and Pattern Recognition, 2005, 688-695.*

[5] A. Vailaya, M. Figueiredo, A. Jain, & H. J. Zhang. *Image Classification for Content-Based Indexing, IEEE Transactions on Image Processing, 2001, 117-130.*

[6] A. Nefyodov *Method for image classification into indoor-outdoor classes, Russian patent application 2006136861, October 18, 2006.*

[7] M. Liu, P. Yuan, R. S. JR. Turner. *Automatic analysis and adjustment of digital images with exposure problems, US Laid-Open Patent Application 2004/0190789.*

[8] M. Rychagov, S. Efimov *Image processing device to determine image quality and method thereof, RU patent application 2005126348 from August 19, 2005; US patent application 2007/0041657 from February 22, 2007.*

About the authors

Dr. Sergey V. Efimov received his MS degree in physics at Moscow Institute of Physics and Technology (State University) in 1989 and his PhD degree in remote sensing from the same university in 1993. He was the head of Space Image Processing Laboratory at Russian Scientific Research Center of Space Hydrometeorology "Planeta" since 1995 to 2002. In 2004, Dr. Sergey V. Efimov joined Image Enhancement Technology Group, Samsung Research Center, Moscow, Russia. His contact email is sergei.efimov@samsung.com.

Dr. Alexey V. Nefyodov received his MS degree in Applied Mathematics, Computer Science in 2001, and his PhD degree in Discrete Mathematics and Cybernetics in 2005 from the Moscow Lomonosov State University. Since 1999, his basic research and work experience is in the area of pattern recognition, image processing and software development. As a researcher, software engineer, and principal investigator, he worked in Russian and Italian research institutes, software developing companies and in Samsung Research Center in Moscow. He is currently working as Research Associate in the University of Liverpool, UK. His contact e-mail is anef@mail.ru.

Dr. Michael N. Rychagov received his MS degree in physics from Department of Physics at Lomonosov Moscow State University, Russia in 1986, PhD degree and Dr. Sc. degree from the same university in 1989 and 2000 correspondingly. Since 1989, he has been involved in R&D and teaching on Faculty of Electronic and Computer Engineering at Moscow Institute of Electronic Technology (Technical University). In 2004, Dr. Michael N. Rychagov joined Samsung Research Center, Moscow, Russia, where he is currently group leader of Image Enhancement Technology and Video Signal Processing Groups. He is member of IS&T and IEEE Societies. His contact email is michael.rychagov@samsung.com.