ADAPTIVE ILLUMINATION CORRECTION ALGORITHM BASED ON RETINEX TECHNOLOGY FOR CAMERA TRAP IMAGES

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ABSTRACT:

Camera traps generating a huge number of images help to study and monitor the wildlife. However, camera traps work at any time of the day and under any weather conditions. Therefore, many images have low or high illumination, blurring, and other defects. This complicates image analysis by both humans and computer systems. In this study, we develop an adaptive illumination correction algorithm based on a modified Multi-Scale Retinex (MSR). First, we accelerate computation by using recursive implementation of the Gaussian filter and utilizing look-up tables to find logarithms and new brightness values. Second, response of the MSR function is transformed by a modified threshold normalization to improve image quality. The upper and lower thresholds are calculated based on statistical information. Finally, we offer automatic adjustment of parameters depending on the area of the image in order to increase usability. Proposed algorithm was tested with various settings on a set of images obtained from camera traps. Experimental results show a high potential for its application.

1. INTRODUCTION

In recent years, image analysis has been actively used to study and protect natural ecosystems, including individual species of animals threatened with extinction. These images are obtained by camera traps which are digital cameras with an infrared motion sensor. Due to their principle of operation, camera traps able to extract a large amount of data in a non-invasive way.

Unfortunately, this method of extracting data has its drawbacks. Since generated set of images is huge, it becomes quite difficult for a specialist to analyze it. Many systems have been developed to facilitate this work (Camera Base, 2015; Yousif et al., 2019). These systems allow both initial evaluation and cataloguing, as well as annotation of images (manually or automatically). Additionally, there are experimental systems and their parts aimed at localizing animals to reduce the volume of analyzed images (Zotin and Proskurin, 2019).

However, images from camera traps may have an uneven brightness distribution and low contrast depending on the time of day and weather conditions. This increases the complexity of image analysis by both humans and computer systems. Existing systems do not improve image quality, so that a specialist can more correctly evaluate it. There are algorithms and libraries for this, but its use often requires additional parameter adjustments for a specific image resolution, scene types, etc.

In this paper, we propose a method based on the modified Retinex algorithm to solve these problems. Modifications are aimed at accelerating calculations, improving image quality, and automatic adjustment of parameters. Usage of pre-calculated values stored in look-up tables at various stages, as well as the recursive implementation of the Gaussian filter (Young and Vliet, 1995), accelerate the execution of the algorithm. Image quality improvement is achieved by brightness correction in HSV color model followed by scaling Retinex function response to the displayed range in various ways. The best result shows developed scaling algorithm based on the assessment of the standard deviation and coverage of Retinex function response histogram area. Proposed algorithm parameters are adjusted based on the resolution of the image, and statistical information of Retinex function response.

The rest of the paper is organized as follows. In Section 2, the related works in illumination correction are briefly reviewed. The description of our proposed modified Retinex algorithm is presented in Section 3. Some empirical results and discussions are demonstrated in Section 4. Finally, conclusions are drawn in Section 5.

2. RELATED WORKS

There are many algorithms to solve the problem of uneven illumination, among which we can distinguish a group of algorithms based on Retinex technology (Parihar and Singh, 2018).

Single-Scale Retinex (SSR) is the most basic method of Retinex algorithms. In SSR, the illumination is estimated by convolving a Gaussian filter with an input image, and the resulting scene reflectance is obtained in log-scale. The mathematical computation can be described by following expression:

$$R_{SSR_i}(x,y,\sigma) = log\big(I_i(x,y)\big) - log\big(I_i(x,y) * G(x,y,\sigma)\big), \quad (1)$$

where $I_i(x,y)$ = intensity value of the x and y coordinates for the i-th color channel of the RGB model
$G(x,y,\sigma)$ = Gaussian
σ = scale parameter or blur coefficient
$*$ = convolution operation

It should be noted that it is necessary to select right blur coefficient in order to obtain the best result. Also, convolution

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with Gaussian filter is independent of the image content. The influence that a pixel has on another one depends only their distance in the image, not on the actual image values.

Instead of Gaussian filter we can use bilateral filter that takes into account difference in value with the neighbors to preserve edges while smoothing (Paris et al., 2009). The key idea of the bilateral filter is that for a pixel to influence another pixel, it should not only occupy a nearby location but also have a similar value. The drawback is a significant increase in calculations.

Multi-Scale Retinex (MSR) is an extension of SSR. It combines the merits of different Retinex scales (small, medium and large) to achieve a balance between dynamic range compression and tonal rendition. Usually, at least 3 scale levels are selected with their own blur coefficient value at each. An advanced version of the classic MSR algorithm uses different weights to sum SSR functions response:

$$R_{MSR}(x,y,\sigma) = \sum_{k=1}^{n}\left(w_k \cdot R_{SSR_k}(x,y,\sigma_k)\right), \qquad (2)$$

where n = number of scales
$\sigma = \{\sigma_1, \sigma_2, ..., \sigma_n\}$ = vector of the blurring coefficients
w_k = weight associated with k-th scale, where $w_1 + w_2 + ... + w_n = 1$
$\mathrm{R_{SSR_k}}$ = k-th component of the scale

All this increases the number of configurable parameters: the number of levels, the blur coefficient for each level, and the weighting coefficients to form MSR function response.

Although MSR gives better results by combining dynamic range compression and colour rendition, it suffers from desaturation (greying-out) of uniform parts. One way to solve this problem is the use of color restoration function, which led to Multi-Scale Retinex with Color Restoration (MSRCR) development (Wang et al., 2015). The mathematical representation of MSRCR calculation formula can be written as:

$$R_{MSRCR}(x,y,\sigma) = C_i(x,y) \cdot R_{MSR}(x,y,\sigma), \qquad (3)$$
$$C_i(x,y) = \beta \cdot log\left(\alpha \cdot \frac{I_i(x,y)}{\sum_{i=1}^{3} I_i(x,y)}\right),$$

where $C_i(x,y)$ = color restoration function for the i-th color channel of the RGB model
$I_i(x,y)$ = intensity value of the x and y coordinates for the i-th color channel of the RGB model
β = gain constant
α = parameter controlling the strength of nonlinearity

MSRCR algorithm gives a good color rendering, however, it can't work well for details in the dark areas. To solve this problem other versions of Retinex algorithm were proposed. For example, algorithms that use color spaces that have explicit brightness and chroma components, such as YIQ (Jiao and Xu, 2009), HIS (Gao et al., 2015), and HSV (Zotin, 2020).

Since the result of the Retinex function can yield negative and positive values with arbitrary bounds, the obtained range of values has to be transformed into the display domain [0, 255]. Various methods can be used for scaling. One way is based on the difference between minimum and maximum values (MinMax):

$$I_{MSR}(x,y,\sigma) = Cl255\left(\frac{R_{MSR}(x,y,\sigma) - R_{min}}{R_{max} - R_{min}} \cdot 255\right), \qquad (4)$$

where $Cl255$ = function that limits the output to the display domain [0, 255]
R_{min}, R_{max} = minimum and maximum of Retinex response

Other way is based on gain/offset coefficients, which requires the configuration of additional parameters:

$$I_{MSR}(x,y,\sigma) = R_{MSR}(x,\ y,\ \sigma) \cdot k_{gain} + k_{offset} \qquad (5)$$

In addition, we can use different algorithms of histogram transformation, that more evenly re-distribute pixel values in the display domain (Raju et al., 2013). One of the algorithms is the well-known Balance Contrast Enhancement Technique (BCET), that stretch or compress contrast of the image using parabolic function obtained from the input image (Amjad et al., 2022):

$$I_{BCET} = a(I - b)^2 + c, \qquad (6)$$

where I = input image
a, b, c = coefficients calculated using maximum, minimum, and mean of an image's input and output values

BCET use global information of the image. In some cases, when grayscale distribution is highly localized, this leads to a situation where two very close grayscales might be mapped to significantly different grayscales. This issue is solved in Contrast Limited Adaptive Histogram Equalization (CLAHE) that improves local contrast and edges adaptively in each region (patch) of the image using the local distribution of pixel intensities (Reza, 2004).

3. PROPOSED METHOD

Our method is based on SSR and MSR algorithms calculated for the V channel from the HSV color model. The modified MSR algorithm includes a number of ways to accelerate processing: recursive implementation of the Gaussian filter (Young and Vliet, 1995); look-up tables to perform computational procedures in MSR function. For the latter, a scheme is implemented that allows to switch from real calculations during logarithms and Retinex response computation to integer ones using a 12-bit representation.

In order to minimize the number of settings in the algorithm, we use automatic adjustment of blur parameters for the MSR function. Blur coefficients are selected as a percentage of the square root of the image area. This decision was due to the fact that camera traps create images in different resolutions (from 1 MP to 16 MP) and with different aspect ratios (4:3, 16:9).

We decided to scale Retinex response in several ways using MinMax, BCET, and CLAHE algorithms, as well as StdPrMinMax – our threshold normalization that applies the T_{Lo} and T_{Hi} thresholds according to the expression:

$$I_{New}(x,y,\sigma) = Cl255\left(\frac{R_{MSR}(x,y,\sigma) - T_{Lo}}{T_{Hi} - T_{Lo}} \times 255\right), \qquad (7)$$

An estimate based on statistical information is used to determine the thresholds. For this, the minimum R_{min}, maximum R_{max}, mean R_{avg}, and standard deviation SD of Retinex response are determined. Range based on standard deviation [Rsd_{Lo}, Rsd_{Hi}] is formed according to the expression:

$$Rsd_{Lo} = \max\left(R_{\min}, \left(R_{avg} - 3 \times SD \right) \right), \quad Rsd_{Hi} = \min\left(R_{\max}, \left(R_{avg} + 3 \times SD \right) \right) \tag{8}$$

Additionally, we determine the boundaries of the range [Rp_{Lo}, Rp_{Hi}] by taking into account 97% occurrence in the response. The value of 97% was found in the course of an experimental study and showed the best results. The final values of the T_{Lo} and T_{Hi} thresholds are selected as follows:

$$T_{Lo} = \min\left(Rsd_{Lo}, Rp_{Lo} \right), \quad T_{Hi} = \max\left(Rsd_{Hi}, Rp_{Hi} \right) \tag{9}$$

4. EXPERIMENTS AND RESULTS

The experimental study was conducted using a set of images captured by camera traps in different regions of "Ergaki" Nature Park. The set includes images of the following categories: images with low brightness, images with high or medium brightness and low contrast, images with low illumination of the object of interest and the presence of a high brightness component, images with a high brightness difference. Examples of images are shown on Figure 1a. In the following subsections, we describe metrics and programs used for evaluation, and results of experiments.

4.1 Metrics

Various metrics were used to evaluate the effectiveness of the developed algorithms. In order to calculate them, masks were formed for each image I: Mo – object of interest (Figures 1c); Mr – region around object of interest (Figures 1d); Mb – box with object of interest (Figures 1e).

All metrics can be divided in three parts. First part aimed at contrast evaluation. This metrics were calculated separately before and after the algorithm was applied. Each metric from this part was computed for channel V from the HSV color model, as well as separately for each RGB channel followed by averaging:

- Mean value of pixels from box with object of interest (hereinafter such pixels referred to as I_{Mb}):

$$\mu\left(I_{Mb} \right) = \frac{1}{RC} \sum_{i=1}^{R} \sum_{j=1}^{C} I_{Mb}(i,j), \tag{10}$$

where R, C = number of rows and columns of I_{Mb}

- RMS – Root Mean Square of I_{Mb} is defined as the standard deviation of the pixel intensities (Peli, 1990):

$$RMS\left(I_{Mb} \right) = \sqrt{\frac{1}{RC} \sum_{i=1}^{R} \sum_{j=1}^{C} \left(I_{Mb}(i,j) - \mu\left(I_{Mb} \right) \right)^2} \tag{11}$$

- Weber contrast calculated for object of interest and region around this object (Peli, 1990):

$$Weber(I(Mo, Mr)) = \frac{\left| \mu\left(I_{Mo} \right) - \mu\left(I_{Mr} \right) \right|}{\mu\left(I_{Mr} \right)} \tag{12}$$

Second part of metrics evaluates overall quality of images. It also was calculated separately before and after the algorithm was applied, but for RGB color model:

- BRISQUE – Blind/Referenceless Image Spatial Quality Evaluator (Mittal et al., 2012). BRISQUE compare image to a default model computed from images of natural scenes with similar distortions. A smaller score indicates better perceptual quality.
- NIQE – Natural Image Quality Evaluator (Mittal et al., 2013) is a blind quality analyzer that makes use of measurable derivations from statistical regularities perceive in natural images without training on human-rated distorted images. It is based on the construction of a quality aware collection statistical features depends on simple and successful space domain natural scene statistic model. These features are derived from an entity of natural, undistorted images. The smaller NIQE score means better perceptual quality.
- PIQE – Perception Image Quality Evaluator (Venkatanath et al., 2015) is non-reference image quality evaluation method which uses the mean subtraction contrast normalization coefficient to calculate the image quality score. To mimic human behavior, quality estimates only from perceptually significant spatial regions. A smaller score indicates better perceptual quality.

The third part of the metrics was a comparative assessment of image quality by experts. First of all, the visibility and quality of the object of interest was evaluated. It was carried out by ranking the original and processed images.

4.2 Program for evaluations

In order to find the best modifications, we have developed a system consisting of two programs. The first is written in Python using of OpenCV library. The main goal is to select parts of the Retinex algorithm from various groups and assess the resulting combinations using first part of metrics. The groups are as follows:

1. Retinex algorithm {SSR, MSR}.
2. Blur filter {Gaussian filter, Bilateral filter}.
3. Scaling {MinMax, BCET, CLAHE, StdPrMinMax}.

Parts of the algorithm were tested with different parameter settings. The total number of combinations is more than 200. The second program is written in Matlab and calculates second part of metrics for generated images.

The best result was shown by MSR with Gaussian filter, in which the blur coefficients are taken as 5%, 10%, and 15% from the root of the image area. Examples of images processed by proposed algorithm are shown on Figures 1b.

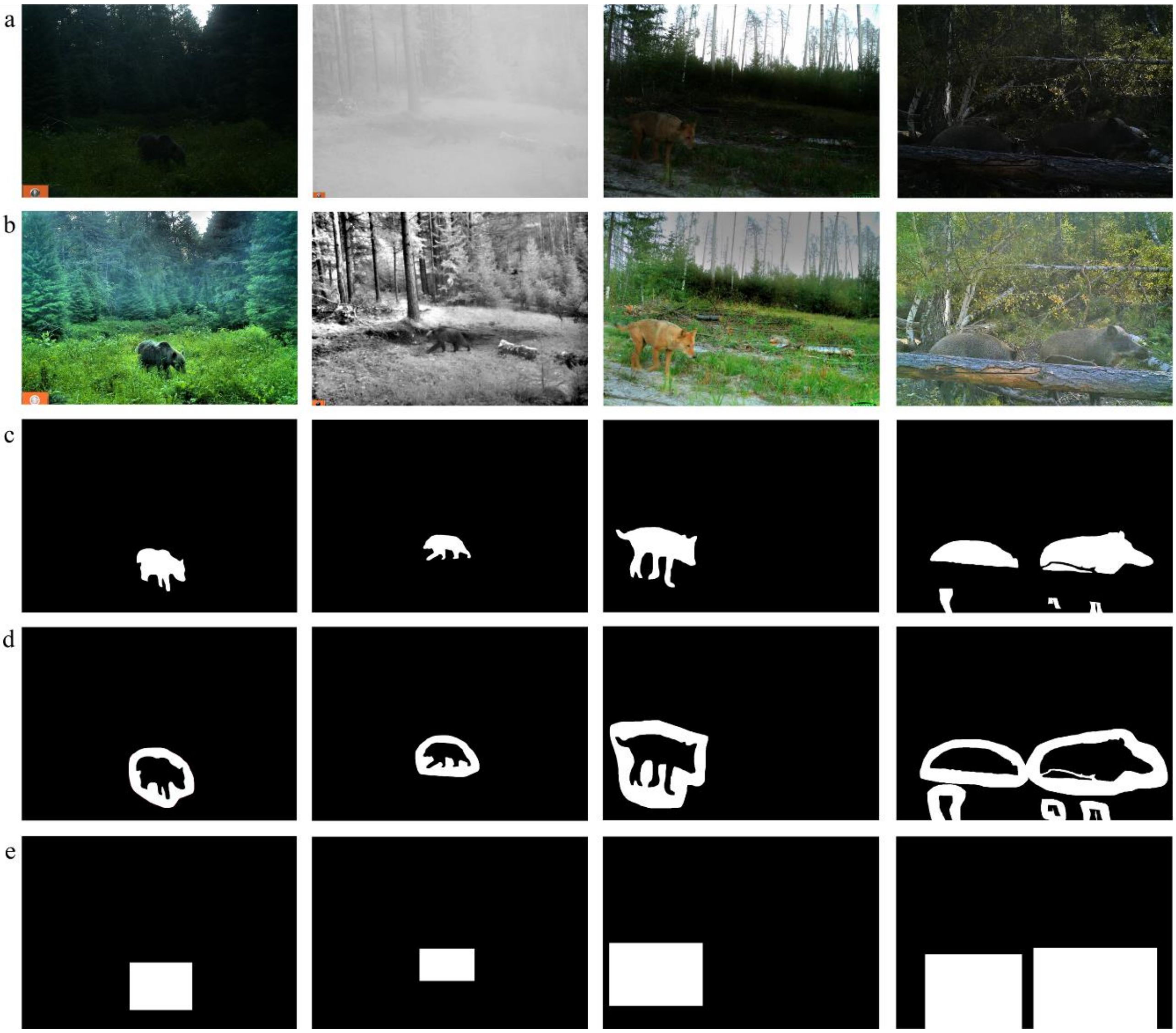

Figure 1. Example of illumination correction using proposed algorithm: a) original images, b) images after correction, c) object of interest, d) region around object of interest, e) box with object of interest.

Figure 2. Image in2_bear before and after MSR with Gaussian filter and following scaling: a) original image, b) MinMax, c) BCET, d) CLAHE, e) StdPrMinMax.

Figure 3. Image in4_boar before and after MSR with Gaussian filter and following scaling: a) original image, b) MinMax, c) BCET, d) CLAHE, e) StdPrMinMax.

4.3 Experimental results

The presence of several categories of original images with uneven illumination, as well as a large number of possible combinations of illumination correction, generated a huge amount of data. In this subsection, we will give a small part of the results obtained for MSR with Gaussian filter and different scalings applied to images in2_bear (Figures 2) and in4_boar (Figures 3).

First, we present the results of calculations for the first group of metrics. The data for V channel of the in2_bear image is shown in Table 1. Since the original image is in grayscale, the assessments for the RGB color model will be the same. It can be seen that in the original image, most of the pixels have similar values (this is indicated by low RMS value), and the object of interest almost merges with the background (low Weber contrast value). The use of BCET and CLAHE scalings improve RMS by 1.35 and 1.25 times, Weber contrast by 2.1 and 1.9 times, respectively. MinMax degrades contrast. Unlike these algorithms, proposed StdPrMinMax increases the RMS by 6.9 times, and Weber contrast by 10.6 times.

Tables 3-4 show contrast estimates for the in4_boar image. All algorithms have increased the brightness of the almost black source image. For channel V from HSV color space, MinMax and BCET increase RMS contrast by 1.5 times, and CLAHE and StdPrMinMax by 2.6 times. For the RGB color space, these values are greater by 0.3-0.4. Weber contrast for all algorithms degrades, since in original image tree trunk is much brighter than boars, while after processing their brightnesses are equalized. However, visually boars become much more noticeable.

Results for the second group of metrics for images in2_bear and in4_boar are presented in tables 4 and 5, respectively. For all metrics, lower value means better image quality. It can be seen that best result was shown by StdPrMinMax algorithm, which improves in2_bear image quality according to BRISQUE and PIQE metrics by 26.8 % and 13.8 %, respectively. At the same time, NIQE metric shows a slight decrease. In the case of in4_boar image, CLAHE algorithm increases BRISQUE and PIQE metrics by 11.7% and 20.1%, respectively, while StdPrMinMax shows quality improvement only for PIQE metric (+21.5%). For most combinations, there is a slight deterioration in NIQE metric. This may be consequence of the fact that algorithms distort the natural image's structure. For example, in in2_bear image, area of trees becomes overly contrasting, but object of interest is more visible.

Image	μ	RMS	Weber
in2_bear	188.6	4.752	0.035
MinMax	125.0	2.165	0.024
BCET	122.1	6.434	0.074
CLAHE	124.7	5.912	0.065
StdPrMinMax	106.2	32.769	0.368

Table 1. Results for first part of metrics calculated for V channel of in2_bear

Image	μ	RMS	Weber
in4_boar	21.1	15.338	0.288
MinMax	125.4	22.423	0.067
BCET	125.3	22.664	0.069
CLAHE	122.5	39.992	0.115
StdPrMinMax	125.0	39.566	0.117

Table 2. Results for first part of metrics calculated for V channel of in4_boar

Image	μ	RMS	Weber
in4_boar	18.6	14.280	0.250
MinMax	109.9	27.760	0.018
BCET	109.9	27.930	0.018
CLAHE	107.4	40.380	0.066
StdPrMinMax	109.9	40.040	0.068

Table 3. Averaging results for first part of metrics calculated for each RGB channel of in4_boar

Image	BRISQUE	NIQE	PIQE
in2_bear	50.18	5.77	71.14
MinMax	44.95	7.03	81.38
BCET	49.25	5.17	71.14
CLAHE	43.63	7.49	83.30
StdPrMinMax	36.72	6.21	61.34

Table 4. Results for second part of metrics calculated for in2_bear

Image	BRISQUE	NIQE	PIQE
in4_boar	33.83	4.38	26.70
MinMax	31.16	4.66	22.62
BCET	31.03	4.64	22.55
CLAHE	29.86	4.55	21.34
StdPrMinMax	31.88	4.75	20.96

Table 5. Results for second part of metrics calculated for in4_boar

Image	in2_bear	in4_boar
Original	4	5
MinMax	5	3
BCET	3	4
CLAHE	2	1
StdPrMinMax	1	2

Table 6. Ranks assigned to images by experts.

Information about scores from the third group of metrics for in2_bear and in4_boar images is shown in Table 6. It follows from obtained data that best result is achieved using CLAHE and StdPrMinMax algorithms.

Additionally, we measured the speed of various MSR steps using images ranging in sizes from 1280×720 to 4608×3456. It was found that the use of look-up tables increases the speed of calculating the Retinex response by 4.2-4.9 times, and scaling with StdPrMinMax algorithm speeds up by 4.7-5.3 times (with increase in image size, the acceleration drops slightly).

5. CONCLUSIONS

In this study, we propose adaptive illumination correction algorithm based on a modified Multi-Scale Retinex (MSR). In order to reduce computational cost, we use recursive calculation of the Gaussian filter, and look-up tables to find logarithms and new brightness values. The use of look-up tables accelerate calculation of Retinex function response by 4.2-4.9 times. The scaling StdPrMinMax speedup by 4.7-5.3 times. We also offer automatic adjustment of parameters depending on the area of the image. The best result was shown for blur coefficients taken equal to 5%, 10%, and 15% of the root of the image area. To improve image quality, we transform response of the MSR function by well-known algorithms MinMax, BCET, and CLAHE, as well as modified threshold normalization. In the latter, the upper and lower thresholds are calculated based on statistical information. An experimental study, in which we assess different combination of the Retinex algorithm parts, shows best results for MSR with Gaussian filter and StdPrMinMax or CLAHE scaling.

REFERENCES

Amjad, R.K., Tanzila, S., Tariq, S., Seng-phil, H., 2022. Cloud-Based Framework for COVID-19 Detection through Feature

Fusion with Bootstrap Aggregated Extreme Learning Machine. *Discrete Dynamics in Nature and Society*, 2022, 1-7. doi: 10.1155/2022/3111200

Gao, H., Wei, P., Ke, J., 2015. Color enhancement and image defogging in HSI based on Retinex model. *Proceeding of the SPIE 9622, International Conference on Optical Instruments and Technology: Optoelectronic Imaging and Processing Technology*, 962203, 8 p. doi: 10.1117/12.2193264

Jiao, Z., Xu, B., 2009. An Image Enhancement Approach Using Retinex and YIQ. *International Conference on Information Technology and Computer Science 2009*, 476-479. doi: 10.1109/ITCS.2009.104

Mittal, A., Moorthy, A.K., Bovik, A.C., 2012. No-Reference Image Quality Assessment in the Spatial Domain. *IEEE Transactions on Image Processing*, 21(12), 4695-4708. doi: 10.1109/TIP.2012.2214050

Mittal, A., Soundararajan, R., Bovik, A.C., 2013. Making a “completely blind” image quality analyzer. *IEEE Signal Processing Letters*, 20(3), 209-212. doi: 10.1109/LSP.2012.2227726

Parihar, A.S., Singh, K., 2018. A study on Retinex based method for image enhancement. *2nd International Conference on Inventive Systems and Control*, doi: 10.1109/ICISC.2018.8398874

Paris, S., Kornprobst, P., Tumblin, J., Durand, F., 2009. Bilateral Filtering: Theory and Applications. *Foundations and Trends in Computer Graphics and Vision*, 4(1), 1-73. doi: 10.1561/0600000020

Peli, E., 1990. Contrast in complex images. *Journal of the Optical Society of America A*, 7(10), 2032-2040.

Raju, A., Dwarakish, G.S., Reddy, V., 2013. A Comparative Analysis of Histogram Equalization based Techniques for Contrast Enhancement and Brightness Preserving. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 6(5), 353-366. doi: 10.14257/ijsip.2013.6.5.31

Reza, A.M., 2004. Realization of The Contrast Limited Adaptive Histogram Equalization (Clahe) For Real-Time Image Enhancement. *The Journal of VLSI Signal Processing-Systems for Signal, Image, and Video Technology*, 38(1), 35-44.

Tobler, M., Camera Base, 2015. Software, Version 1.7, San Diego Zoo Global Institute for Conservation Research. atrium-biodiversity.org/tools/camerabase/ (14 January 2023).

Venkatanath, N., Praneeth, D., Bh, M.C., Channappayya, S.S., Medasani, S.S., 2015. Blind image quality evaluation using perception based features. *Twenty First National Conference on Communications*. doi: 10.1109/NCC.2015.7084843

Young, I.T., Vliet, L.J., 1995. Recursive implementation of the Gaussian filter. *Signal Processing*, 44(2), 139-151. doi:10.1016/0165-1684(95)00020-E

Yousif, H., Yuan, J., Kays, R., He, Z., 2019. Animal Scanner: Software for classifying humans, animals, and empty frames in camera trap images. *Ecology and Evolution*, 9(4), 1578-1589.

Wang, J., He, N., Lu, K., 2015. A new single image dehazing method with MSRCR algorithm. *Proceedings of the 7th International Conference on Internet Multimedia Computing and Service* (ICIMCS '15), Article 19, 1-4. doi.org/10.1145/2808492.2808511

Wang, Z., Simoncelli, E.P., Bovik, A.C., 2003. Multiscale structural similarity for image quality assessment. *The Thrity-Seventh Asilomar Conference on Signals, Systems & Computers*, 2, 1398-1402. doi: 10.1109/ACSSC.2003.1292216

Zhang, R., Isola, P., Efros, A.A., Shechtman, E., Wang, O., 2018. The Unreasonable Effectiveness of Deep Features as a Perceptual Metric, Computer Vision and Pattern Recognition. doi: 10.48550/arXiv.1801.03924

Zotin, A.G., Proskurin, A.V., 2019. Animal detection using a series of images under complex shooting conditions. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.*, XLII-2/W12, 249-257.

Zotin, A.G., 2020. Fast algorithm of image enhancement based on multi-scale retinex. *Int. J. Reasoning-based Intelligent Systems*, 12(2), 106-116.