Edge Based Image Comparison and Noise Removal

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Abstract

PSNR (Peak Signal to Noise Ratio) metric is typically used to estimate difference between two given images. Recent time more reliable metric (SSIM – Structural Similarity) was introduced to detect image changes/noise/etc. This paper introduces more advanced approach for the image difference measurement based on weighted sum of the image structure estimation and edges detection. Proposed metric (ESSIM – Edgeted Structural Similarity) is more close to the human image difference perception; it provides strong emphasize on pixels near edges. The paper illustrates two image modification cases where PSNR and SSIM cannot find difference between images, but proposed metric can do it. Also this paper introduces a novel image noise removal approach based on the weighted mixture of bilateral method and advanced edge detection approach.

Keyword: *Image Similarity; Image Processing; Edge Detection; Noise Removal; Image Quality Metrics;*

1. PREVIOUS WORKS

Image noise removal techniques are widely used for many human activities: professional and amateur photography, aerospace photography, medical images processing, images classification, face detection, etc. To estimate quality of a method for noise removal, you need to do the following pipeline. On the first step to get from somewhere a source image with more or less good quality. Then RGB color information is converted into YCrCb or YUV or other color space, where color intensity information is concentrated in the one channel (not in 3 channels like in RGB color space). On the second step you should introduce some artificial noise into the image. On the third step the method under testing is applied to the “dirty” image, so denoised image is produced. On the fourth, last step, the denoised image is compared with the source image: the less difference, the better noise removal quality. It is very important to use good metrics for image similarity / difference estimation. In the [2] there is a good review of popular image quality metrics, started from simplest PSNR and continued to more complicated techniques. There are also very interesting approaches proposed, but not all of them are implemented. Implementation of one idea - using edge-based measurement - is described in this paper. The paper [4] gives a prove that SSIM measurement is more natural in comparison with PSNR.

Nowadays there are a lot of image removal techniques, and modern approaches try to receive excellent denoising quality for reasonable time. Most of simple convolution methods with static convolution matrix provide very fast image denoising, but unfortunately, add significant blurring on the edges. To keep edges structure is very important for human perception. Bilateral filtration [5] is more or less good solution for this task. We propose some improvements into this well known method to reach better denoising results.

2. IMAGE DIFFERENCE CALCULATION APPROACH

Using SSIM measurement (described in [4]) as a basis, we will modify calculation a little bit and introduce the new coefficient, significantly affecting the result value. According to [2, 4] and many other sources, for given two images P_x and P_y SSIM calculation sequence is:

$$\mu_x = \frac{1}{W*H}\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} P_x(i,j) \quad \mu_y = \frac{1}{W*H}\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} P_y(i,j)$$

where W, H – image dimensions (should be the same for both compared images). Here μ_x, μ_y - so called mean values for images P_x and P_y. After that we can calculate value, which characterizes contrast for each image:

$$C_x = \frac{1}{W*H-1}\sum_{j=o}^{H-1}\sum_{i=0}^{W-1}\left[P_x(i,j)-\mu_x\right]^2$$

$$C_y = \frac{1}{W*H-1}\sum_{j=o}^{H-1}\sum_{i=0}^{W-1}\left[P_y(i,j)-\mu_y\right]^2$$

We can also calculate correlation between images, using the following formula:

$$R = \frac{1}{W*H-1}\sum_{j=0}^{H-1}\sum_{i=0}^{W-1}\left|P_x(i,j)-\mu_x\right| * \left|P_y(i,j)-\mu_y\right|$$

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or each image we have 3 feature-related values, and can calculate three coefficients, characterizing luminance, contrast and structure (covariance) differences between images:

$$K_l = \frac{\left(2\mu_x\mu_y + C_1\right)}{\left(\mu_x\mu_x + \mu_y\mu_y + C_1\right)} \quad K_c = \frac{\left(2C_xC_y + C_2\right)}{\left(C_xC_x + C_yC_y + C_2\right)}$$

$$K_s = \frac{\left(R + C_3\right)}{\left(C_xC_y + C_3\right)}$$

where C_1, C_2, C_3 – constants to avoid division by zero.

Resultant SSIM value will be multiplication of previous coefficients K_l, K_c and K_s. Below, in the section 4, we will show significant drawbacks of SSIM criterion.

Now let us imagine that for any input image we can build the image which describes edges, detected in the input. Values close to 0, describe smooth image areas; values close to 1, describe strong edges. Talking “edges” we assume significant intensity difference in neighbourhood pixels. There are a lot of possibilities how we can calculate edge map. Adding weights to the contrast and correlation calculation, we can introduce edge-dependant contrast and correlation:

$$C_x = \frac{\sum_{j=o}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)\left[P_x(i,j)-\mu_x\right]^2}{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)}$$

$$C_y = \frac{\sum_{j=o}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)\left[P_y(i,j)-\mu_y\right]^2}{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)}$$

where W_x – weight matrix with values in [0..1], describing edge feature for pixel $P_x(i,j)$. We will use only one weight matrix, created from the first image, to create dependence on edges. In this approach, the first image assumed as original and "clean" image, the second one is the result of denoising procedure. Edge-weighted correlation will be calculated as:

$$R_w = \frac{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)\left[P_x(i,j)-\mu_x\right]*\left[P_y(i,j)-\mu_y\right]}{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)}$$

Also, we introduce contrast correlation (D) and weighted contrast correlation (D_w):

$$D = \frac{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} \left[\left(P_x(i,j)-\mu_x\right)-\left(P_y(i,j)-\mu_y\right)\right]^2}{W*H-1}$$

$$D_w = \frac{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)\left[\left(P_x(i,j)-\mu_x\right)-\left(P_y(i,j)-\mu_y\right)\right]^2}{\sum_{j=0}^{H-1}\sum_{i=0}^{W-1} W_x(i,j)}$$

For the new introduced image characteristics we will calculate a special coefficient, showing relationship between D and D_w:

$$K_w = \frac{\left(D+C_4\right)}{\left(D+D_w+C_4\right)}$$

For the images which have noticeable difference in edge areas, K_w drops down to zero. Finally, we can calculate resultant ESSIM value:

$$ESSIM = K_l * K_c * K_s * K_w$$

ESSIM value has the same meaning, as SSIM: 0 means absolutely different images, 1 means the same images. The more ESSIM close to 1, the more similar images are.

3. EDGES CALCULATION

In the previous section we have introduced special matrix W_x, which describes edges existence for each original image pixel. For the sake of simplicity we can calculate W_x values, based on [7] with sequence of the following operations. First, we will smooth input image in order to roughly remove noise artefacts. For this purpose any smoothing convolution can be applied. Then we calculate two gradient fields: G_x and G_y:

$$G_x(x,y) = \sum_{j=-1}^{+1}\sum_{i=-1}^{+1} P_x(x+i,y+j) * KG_x(1+i,1+j)$$

$$G_y(x,y) = \sum_{j=-1}^{+1}\sum_{i=-1}^{+1} P_y(x+i,y+j) * KG_y(1+i,1+j)$$

where KG_x and KG_y are simple kernel matrices used in convolution:

$$KG_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad KG_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

G_x and G_y values describe intensity gradients in both directions: horizontal and vertical. KG_x and KG_y are well known under the name of Sobel operator kernel. Final "edge" feature value for any image pixel (x,y) can be calculated as:

$$W_x(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2}$$

Fig. 1 and 2 show detected edges, calculated by this formula for different test images (original images are on the left):

Fig. 1 Edges for Caracas and City images

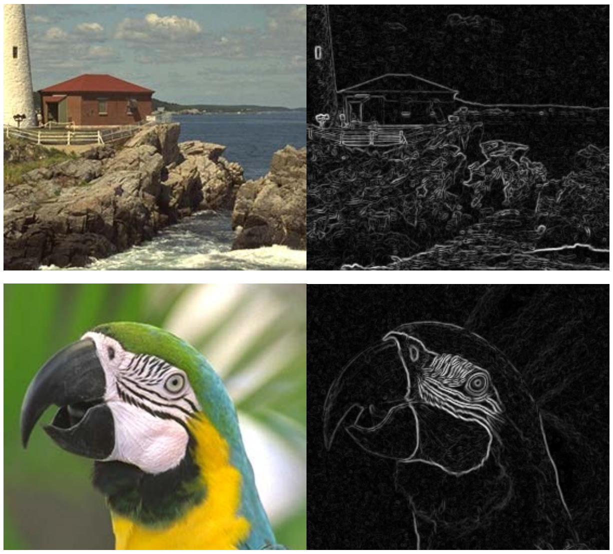

Fig. 2 Edges for Girl, Light House and Macaw images

4. TEST RESULTS

Let us first test sensitivity of the proposed ESSIM metric as compared with well known metrics for a synthetic image. For example, for test image Fig. 3.

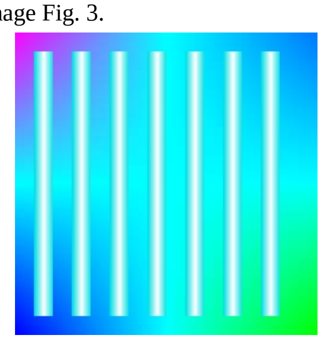

Fig. 3 Test sample image

We will insert artificial white Gaussian noise into this image in two different manners: the first approach will touch input image areas without visible edges; the second approach will change pixels around image edges, as shown on Fig. 4.

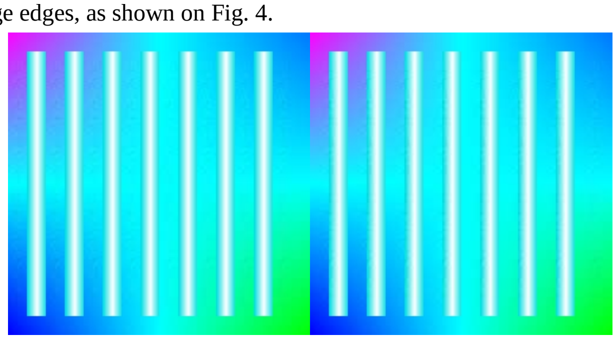

Figure 4: Very similar light modifications, applied to the different areas

In both cases corrupted area has the same size (in pixels), noisy pseudo-random fluctuations are the same too, and both modifications have equal noise range. Important difference between images is the areas, where pixels are modified. It is possible (but not very easy) to notice that right image looks more "corrupted". This impression can be received after edges observation: on the left image they are more "perfect" and human eye can "decide" that left image is of higher quality in comparison with right one. This effect is very close to the well-known Mach bands optical illusion, illustrating that human eye will see the same color in different ways, depending on the edge changes. Very good review of optical illusions can be found in [1] and [3]. Comparison between last two distorted images and original image gives not significant difference both for PSNR and SSIM measurements, but proposed ESSIM measure will detect noticeable difference, as shown in Table 1.

Table 1. Comparison of three image difference criteria for the synthetic image

Image modification	PSNR	SSIM	ESSIM
Noise in non-edge areas	29.53	0.9992	0.9682
Noise in edge areas	29.98	0.9990	0.5088

PSNR estimation detects the right image as more similar to the original than the left one. SSIM measurement shows that both modifications are the same and only ESSIM displays significant difference between two distortions according human perception: right one is more noticeable.

A set of natural test images is shown on Figs 5-7. They are results of various modifications of Girl image (Fig. 2). The differences between these images and source one calculated by three criteria

Fig. 5 Higher contrast image (left); negative image (right)

Fig. 6 Light Gaussian blur; lossy compression

Fig. 7 Light blurring; RGB components modification (R+10, G-5, B-5)

are shown in Table 2.

Table 2. Comparison of three image difference criteria for natural images

Image modification	PSNR	SSIM	ESSIM
Contrast	27.44	0.9767	0.3947
Negative	10.87	0.9454	0.6778
Added Gaussian noise	29.98	0.9892	0.5066
Lossy compression	28.66	0.9886	0.3530
Add light blur	26.43	0.9870	0.2489
RGB channels modification	100.0	0.9997	0.6703

In all cases ESSIM appears to be more sensitive to distortions than two well-known criteria. Of course, image blurring, contrast and loss of details are the strongest distortions affecting edges. We see corresponding large ESSIM differences for these modifications. Last image modification is most interesting: each pixel red color component was increased by 10 (for the color component range [0.255]), and green, blue components were decreased by 5. Both PSNR and SSIM detect no changes in image (but distortion is noticeable by eye), but ESSIM detects significant changes.

Yet one more interesting image comparison is received after RGB components modification (R-=20; G+=10; B+=10), applied to synthetic generated image Fig. 8.

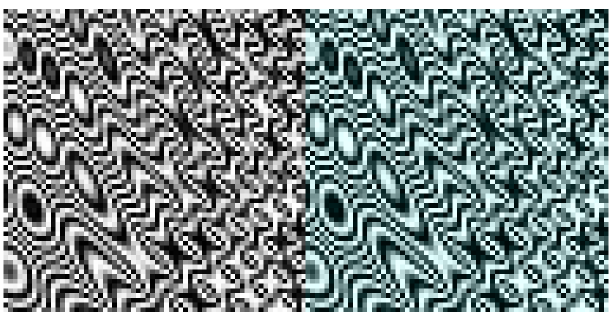

Fig. 8 Synthetic test image (left) and its light rgb components modification

Here SSIM value is equal to 0.9995 (which means that images are almost the same), but ESSIM is equal to 0.5730.

5. IMAGE NOISE REMOVAL METHOD

Bilateral filtering was introduced in [5] and uses more advanced approach as compared with simple Gaussian weighted non-linear filtration. Tricky data driven weight calculation is a famous way to produce new noise removal algorithms. Based on classical bilateral approach, a special combination of two different bilateral filters is introduced in [6]. Big disadvantage of this method is a hidden weight coefficient calculation based on the difference between medians for neighbouring pair of image pixels. Here we introduce a new approach for weights calculation. Let W and H be image dimensions. Let N – radius of the square shaping neighbourhood around each image pixel (x,y). Neighbourhood area is required to take into account some pixels around (x,y). The size of the neighbourhood area is equal to:

S = (2N+1)(2N+1)

Based on the non-linear filtering, we need to compute the new intensity of the pixel (x,y):

$$P'(x,y) = \frac{\sum_{j=-N}^{N} \sum_{i=-N}^{N} w(i,j) P(x+i, y+j)}{\sum_{j=-N}^{N+1} \sum_{i=-N}^{N+1} w(i,j)}$$

Increasing value of N we make the calculation more "integrated". Negative impact of increasing N is increased calculation time. Classical bilateral filter approach uses the following formula to calculate weights in pixel (x,y) neighbourhood:

$$w(i,j) = e^{-\frac{(i^2+j^2)}{2\sigma_s^2}} e^{-\frac{|P(x+i,y+j)-P(x,y)|^2}{2\sigma_r^2}}$$

Here σ_s and σ_r are so called spatial and radiometric constants, operator | P(x+i,y+j)-P(x,y) | is a squared difference between intensities of central pixel (x,y) and current pixel in its neighbourhood. Formula for w(i,j) calculation shows a simple principle for weight calculation: result weight is depending on two weights components multiplication – spatial and radiometric components. Pixel (i,j) in the neighbourhood of (x,y) will be weighted less with increasing distance between (x,y) and (i,j). Pixel (i,j) will be weighted less if difference between intensity value of this pixel and central pixel will increase, radiometric coefficient will be smaller. Talking simpler, if we have very similar intensities in the pixel (x,y) neighbourhood, we will calculate average intensity for this neighbourhood. If intensity of the central pixel (x,y) differs much from the intensities in its neighbourhood, the weights of neighbourhood pixels will drop down to 0, so in this case value of the central pixel intensity will not be modified by calculation. In our approach we will go one step further: try to compare "edginess" of the central pixel (x,y) and pixel in its neighbourhood (i,j). If the current pixel lies on the same edge area as the central one (the same if both are not on the edge) we will take into account its value and assign "large" weight to pixel (i,j). If the current pixel has different "edginess" as compared with the central one, we will assign low weight in this case. So, for each pixel (i,j) in the neighbourhood of pixel (x,y) we will calculate spatial, radiometric and edginess coefficients:

$$C_s = i^2 + j^2; C_r = |P(x,y) - P(x+i, j+j)|^2$$

$$C_e = |W(x,y) - W(x+i, y+j)|$$

where W(x,y) – edges matrix, created by Sobel method (was described above in section III). Resultant weight can be calculated as:

$$w(i,j) = e^{-\frac{(C_s * C_r * C_e)}{\sigma}}$$

Here, σ is Gaussian constant, affected on "blurring" in resultant image. Important difference between proposed method and classic bilateral filtration is inside multiplication of components (not addition). This will cause stronger impact of a small change in a component on the resultant weight. For the practical implementation it is important to change two parameters of the proposed method: the size of the neighbourhood area (affecting whole integration) and σ value, affecting smoothness (larger values give more blurred result).

6. HIGH ISO NOISED IMAGES PROCESSING

For the synthetic noise added to the good quality images, the proposed edge bilateral method is not so impressive: it is not so strong noticeable visual difference between results of proposed method and classic bilateral filtration. For natural test images the difference is more evident: the proposed method provides less blurring, as it is shown on Figs. 9 and 10.

Fig. 9 Caracas noised image after bilateral filtration (left) and after proposed edge bilateral filtration (right)

Fig. 10 Girl noised image after bilateral filtration (left) and after proposed edge bilateral filtration (right)

Using proposed approach we have applied developed filter to the set of real life high noised digital photos in order to remove noise. Each of Figs 11-13 show source noised picture (no artificial noise added, left) and result of applying proposed denoising filter (right). N is the radius of neighbourhood and σ is the parameter of weight calculation (see formulas in section 5).

Fig. 11 Face high ISO digital image after proposed edge bilateral filtration (N=6, σ=900)

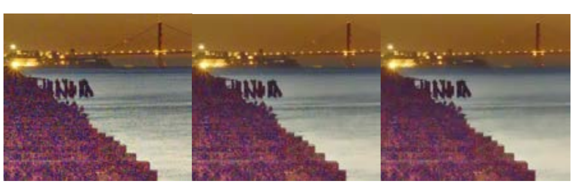

Fig. 12 Pier high ISO image after edge bilateral filtration (N=6, σ=100, 800)

Fig. 13 Nba high ISO image after edge bilateral filtration (N=6, σ=800)

7. RESULTS

Table 3 shows higher edge-preservation quality of the proposed method.

Table 3. Comparison of three image difference criteria for two denoising methods

Test image name	Denoising method	PSNR	SSIM	ESSIM
Caracas	Bilateral	**26.44**	**0.9792**	0.3643
	Edge Bilateral	25.73	0.9735	**0.3896**
City	Bilateral	**26.21**	**0.9900**	0.4167
	Edge Bilateral	25.22	0.9874	**0.4508**
Macaw	Bilateral	27.54	**0.9932**	0.3344
	Edge Bilateral	**27.73**	0.9931	**0.3569**
Girl	Bilateral	27.18	0.9746	0.3625
	Edge Bilateral	**28.46**	**0.9754**	**0.3788**
Light House	Bilateral	**27.04**	**0.9859**	0.4078
	Edge Bilateral	26.58	0.9837	**0.4281**

Better results in each measurement method are shown with bold font. It is easy to see, that ESSIM metrics always correlate to the best denoising method.

8. CONCLUSION

Proposed new image difference metric, based on principles more close to human image vision. Illustrated several cases, where simple metrics can't detect image differences, but proposed metric can do it. Proposed image difference metrics (ESSIM) can be used for non-real time applications, like professional image removal tools/plugins, but it is hard to use it for real-time applications due to high calculation cost. Proposed improvement for bilateral filtration which can save image features on edges and prevent edge blurring.

9. IMAGE SOURCES

Real-life (noisy) images:

Face: Amateur photo, Canon digital camera, courtesy of Ivan Krylov

Pier: Flickr image database

Nba: Digital Photography Forum (http://photography-on-the.net)

Special test images:

Girl, Light House, City, Macaw: Kodak image database (http://r0k.us/graphics/kodak/). Caracas: Flickr image database

10. REFERENCES

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