

Local-adaptive Enhancement of Details in Thermal Images

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Abstract – In this paper two algorithms are compared for local adaptive enhancement of contrast of thermal images. They are a modified adaptive gamma correction and local adaptive multiscale combining. The second is recursively applied at different scales preceded by smoothing with a Gaussian kernel and weighted averaging with consequent combination of resulting images. It is believed that this algorithm is also applicable for details highlighting. The analysis is made over a set of thermal images varying in contrast, details and overall content. Positive results are obtained which prove the applicability of the second approach for real-world implementations.

Keywords – Sharpness Enhancement, Local-adaptive Operator, Gaussian Kernel, Gamma Correction, Thermal Image.

I. INTRODUCTION

Contrast enhancement and image sharpening play a crucial role in digital image processing related to various tasks from tracking vehicles to object spotting, from establishing medical diagnosis to forensic analysis and many more. Two major branches may be followed along the development of these techniques – the local and global approach. The first allows better processing of finer details in images but takes longer times to execute while the global algorithms are faster but lowering the finer details after processing.

In [1] Kim et al. present a histogram equalization algorithm which employs block overlapping for a sequence of images contrast enhancement. It is addressed towards security applications, mainly domestic surveillance, in low light conditions. Results are presented in qualitative manner with image comparison among various other methods with visible increase of the quality.

Stark [2] makes a step further into proposing generalization of the histogram equalization. Using a cumulation function in order to make mapping between local histogram the author achieves to get a wide set of degrees in contrast change – from untouched intensities to complete equalization.

Another approach proposed by Chang and Wu [3] includes analysis of the local standard deviation and then applying histogram transformation. This approach is considered especially effective in medical image processing following radiography.

Despite the high quality images obtained by described

algorithms it becomes necessary over time for a number of applications to have implementations fast enough working in or close to real-time [4, 5].

In our study we are comparing two algorithms, originally developed for contrast enhancement – the adaptive gamma correction [6] and local-adaptive multi-scale contrast enhancement [7]. The testing is oriented specifically towards thermography applications and as the results described below reveal the second approach could be very well used for enhancing the details in such thermos images.

In Section II detailed description of both algorithms are given followed by experimental results in Section III and then a conclusion is made in Section IV.

II. COMPARED ALGORITHMS

Input data:

Grayscale valued digital image with P pixels horizontally and Q pixels vertically. The brightness I varies from 0 to 255 for each pixel. It is located by path and filename. The software implementation needs to find P and Q automatically. If the input file contains a color image, only the brightness component (e.g. Y from the $YCbCr$ color space of a JPG file) is used.

Output data:

The program implementation outputs a non-compressed image to external memory (e.g. HDD) as bmp. If initially the processing started with a halftone image, it must also be a bmp. If it is a colored one, the newly obtained array after processing is the Y component while the color-difference components (Cb and Cr) are the same as those in the original file, and the resulting file is bmp.

A. Adaptive Gamma Correction

Algorithm:

Gaussian filtering is applied to the input image - the σ (standard deviation) needs to be set by the program interface.

For every pixel of the filtered image $i_g(x, y)$ the parameter is:

$$\gamma(x, y) = (i_g(x, y) - 128) / 128. \quad (1)$$

The output image is obtained from the input by the formula:

$$o(x, y) = 255 (i(x, y) / 255) \cdot |\gamma(x, y)|. \quad (2)$$

The difference with the original approach is that in the current realization the gamma is taken as absolute value. Testing proved that negative values close to -1 when $i(x, y)$ is close to 0 leads to overflow of the types used (double) due to the extremely small values of $o(x, y)$. The effect on the image quality at the output is thought to be not less than that of reported results from testing of the initial implementation.

The output image is saved in the same format, e.g. bmp.

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B. Local-Adaptive Multiscale Processing

Specific input parameters:

Proportionality factor - α (fractional coefficient in floating point representation) - is set by the user at startup of the program.

Number of processing scales - k (integer = 1, 2, 3, ...) - set by the user at startup of the program.

Cutting threshold (integer) - $A_{max} = \{0, 255\}$ - set by the user.

Scaling factor - m - integer (2, 3, ...) - set by the user, default is 3.

Algorithm:

The average image brightness is calculated by:

$$M = \text{sum}(I(i, j)) / (P \cdot Q), i = \{0, (P-1)\}, j = \{0, (Q-1)\}. \quad (3)$$

The image is passed k times:

First pass - a 3×3 window is used to scan the entire image starting from its first row and first column, going to the right in the row to the end of the pixel columns, then the window passes to the second row and so on to the end of the last row. For each mask (window) position a calculation is done for the local average brightness of the pixels in the mask, the local standard deviation from the pixel brightness over the same area (the value of each mask pixel is derived from the average mask brightness, all the differences are raised to a second degree and the resulting numbers are added together and the result is divided by the number of pixels in the mask). It is found: $(\alpha \cdot M / s) - 1$. If this number is greater than A_{max} , it is acknowledged as equivalent to A_{max} . If it is less than zero, it is confirmed as equal to zero. The center pixel's brightness in the mask is subtracted from the average of all masks ' a ' and multiplied by $((\alpha \cdot M / s) - 1)$. After all the picture's passes, all newly received values for the brightness in a pre-allocated array in the memory are saved.

Second pass - a $3m \times 3m$ pixel window is used. All processing steps are repeated as in the first pass. All new brightness values are stored in a separate memory array.

Then the scanning continues - the window size is $3m^{(k-1)} \times 3m^{(k-1)}$ pixels. The steps are the same every time and each time the results are saved in a separate array for the new intensities.

Summing the array with original image brightness levels and those from each pass then follows - getting a resultant array of the same size - $P \times Q$ pixels.

Default values:

Example values for initial tests: $\alpha = 0.5$, $m = 3$, $k = 4$ (4 windows with 3×3 , 9×9 , 27×27 and 81×81 pixels), $A_{max} = 100$. Input images use low-contrast images, including infrared ones.

III. EXPERIMENTAL RESULTS

The test set of images contains 10 IR shots (grayscale) with dimensions of 640×512 pixels. They are part of the FREE FLIR Thermal Dataset for Algorithm Training [8] The intensity resolution is 16 bits per pixel. All images are saved in tiff container using LZW compression.

The interface of the implementation for both algorithms is web-based generated by C# tools. Fig. 1 depicts the entry point for the local adaptive gamma correction.



Fig. 1. Adaptive Gamma Correction GUI

The local-adaptive contrast enhancement algorithm at various scales is shown in Fig. 2.

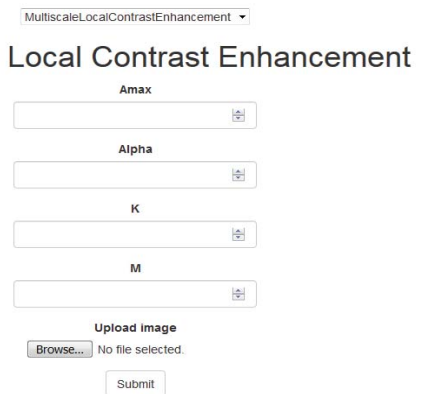


Fig. 2. Multiscale contrast enhancement GUI

Test image 1 is shown in Fig. 3.



Fig. 3. Test image 1 – original

From the results obtained, we notice a multiple increase of the contrast in the algorithm with adaptive gamma correction without major changes in sharpness (Fig. 4).



Fig. 4. Adaptive gamma correction result for image 1

Some images seem to lose part of the details after processing. In the multi-scale processing algorithm, we notice multiple sharpness improvement for all images and contrast enhancement for part of the images (Fig. 5-8).



Fig. 5. Multiscale local-adaptive processing at $k=1$

For image 1, with an adaptive gamma correction, a high illumination of the image is noticeable, but part of the detail is lost - the second car on the right is hard to see, but the details of a darker fan become clearer as a ladder in the distance, for example. After applying the multi-scale pass for image 1, we notice a darker picture than that for the adaptive gamma correction for all passes of 1 - 4. We notice best sharpness when processing with 1 or 2 passes. Better outlines of details in the picture are noticed, for most cases we get the best visibility in 4 passes - some of the pictures can be seen in details that are not visible in the original shots.



Fig. 6. Multiscale local-adaptive processing at $k=2$



Fig. 7. Multiscale local-adaptive processing at $k=3$



Fig. 8. Multiscale local-adaptive processing at $k=4$

The average sharpness over all test images for the tested algorithms is given in Fig. 9.

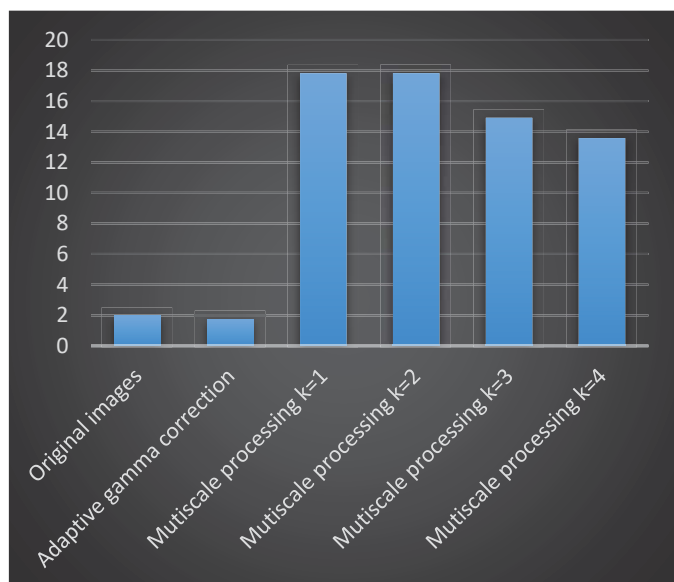


Fig. 9. Resulting image sharpness

For some images, it is clear that the adaptive gamma correction gadget worsens detail, while a multi-step scan algorithm increases it several times.

The RMS contrast for all cases is given in Fig. 10.

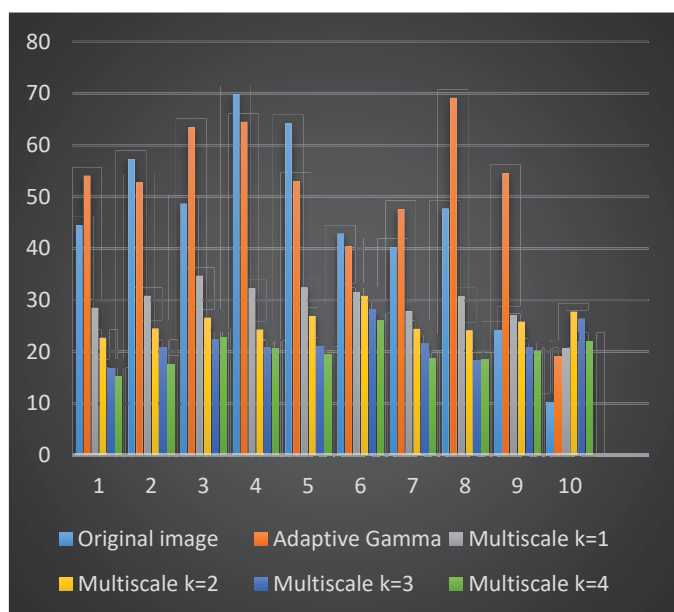


Fig. 10. RMS contrast prior and after processing

From the graph we see that the average image contrast obtained with an adaptive gamma correction algorithm has a higher value than the image after a multi-scale pass.

We could get better values than the multi-scale pass if we provide appropriate mask size, coefficient of proportionality, and cut-off values for each image. There are cases where the default values give the best result – as for image 2 at $k=2$.

The significant difference in RMS contrast for the images processed by the adaptive gamma correction and the multi-scale local-adaptive algorithm is a result mainly on the fact

that the latter operates on a several different scale levels combined at the end. For each of these levels different statistical parameters are found which give good result after applying the transform function – better contrast and details in the same time over the area of the mask. When fusing 2 or more of the areas converted by this approach the details for each are well preserved and leads to even better detailed picture as a final representation but due to interfering effects among areas with varying contrast the overall RMS value tend to be smaller than that of the adaptive gamma correction. A possible solution to this problem is to embed a map of the edges and smaller details in the resulting picture by the multi-scale approach over already enhanced in contrast image by another, possibly globally working, algorithm.

IV. CONCLUSION

In this paper two algorithms for local adaptive contrast enhancement are compared by testing over a set of infra-red images – the adaptive gamma correction and local-adaptive multiscale contrast enhancement. The adaptive gamma correction proves better than the multi-scale approach taking into account the RMS contrast achieved but lots of details are lost from the original image. With the increase of the number of processing scales within the second algorithm the sharpness of the images becomes higher and higher and more and more details become visible. This approach is considered quite promising for large number of applications such as objects tracking, texture extraction, and various patten recognition tasks as a pre-processing step.

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