TILE-BASED FRAMEWORK FOR LOCAL ENHANCEMENT OF BIO IMAGERY

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ABSTRACT

We present a simple framework for image enhancement using local image information. The main idea is to divide the image into small tiles and individually enhance each of these tiles. Enhanced tiles are then mosaicked back together. Our approach is presented for enhancement of fluorescent microscopy images and demonstrates better local contrast preservation and saturation reduction in comparison with traditional global approaches (histogram stretching, equalization or gamma correction).

1. INTRODUCTION

The dynamic range of modern systems employed for biomedical imagery is usually higher than the dynamic range of standard screen display devices used. This discrepancy leads to the problem in the tone mapping from the acquired high dynamic range (HDR) into the lower dynamic range (LDR) of print or screen. The usual approach is to linearly map intensity values into the new dynamic range. In confocal microscopy problems in tone mapping arise when there are areas with different fluorescent responses and certain regions might not be visible or suffer from a severe loss of contrast as shown in Fig. 1. Another problem is uneven illumination which is very common in light microscopy. Different solutions for these problems were proposed and can be classified into two groups: (1) global - spatially invariant mappings, and (2) local - spatially variant operators [1].

Several commonly used global mappings such as histogram equalization usually result in loss of local contrast and oversaturation. Spatially variant operators define regions that are independently enhanced and their quality depends mostly on region outlining.

Our method combines both these approaches by applying mapping on small portions of the image (tiles). The main idea is to divide the image into overlapping tiles and individually enhance each one of them. Enhanced tiles are then mosaicked back together using multi resolution spline technique [2]. Using our framework different tasks can be achieved, such as: dynamic range compression, uneven illumination correction and automatic vignetting (light fall off) correction.

This work was supported by the National Science Foundation award NSF ITR-0331697 and NIH #EY-00888.

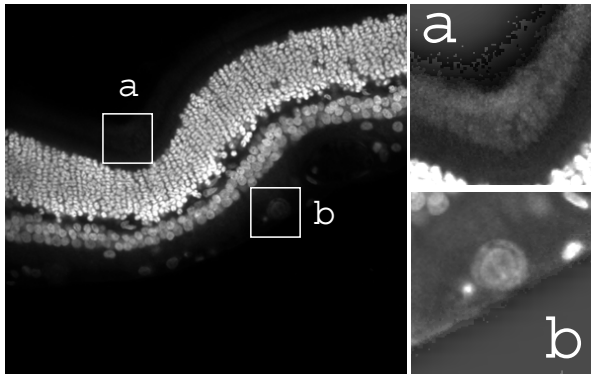

Fig. 1. Fluorescent confocal image of cat retina stained with TOPRO, regions in a) and b) are independently enhanced.

This paper is structured as follows: first we give an overview of previous research in section 2. The the description of the tile-based framework is presented in section 3. In section 4 we describe the contrast enhancement algorithm. Section 5 shows experimental results and we conclude in section 6.

2. BACKGROUND WORK

In this section the overview of previously developed global and local methods is presented. The most naive global mapping linearly normalizes image values into the output device's dynamic range preserving global relative contrast. This can produce regions that are too dark or too bright and may result in a loss of local contrast. Other commonly used global mappings include histogram stretching, gamma correction and histogram equalization. These methods are usually simple and computationally efficient by using look-up-tables. However, their fundamental drawback is over-saturation.

Spatially variant operators, on the other hand, preserve local information by creating separate mappings for each par-

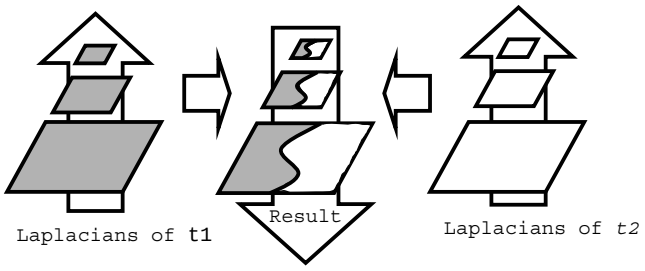

Fig. 2. Multi-resolution spline process, both laplacians are splined and recomposed into blended image.

ticular pixel resulting in a possibility to map two pixels with the same intensities to a different output value. At the same time, two different intensities could be mapped to the same output value. Many methods were inspired by physical vision model called Retinex [3], nevertheless, the main difference is in how to delimit local regions that are being adjusted independently. Proposed solutions include the use of level-set methods [4], magnitudes of the gradients in the image [1] and windows around each image pixel [5] among others. In the last case each pixel is treated as a separate region.

The proposed method combines both approaches by not defining specific regions but instead using small rectangular portions of the image that are adjusted independently.

3. TILE-BASED FRAMEWORK

Our method mixes both previous approaches applying independent mapping for small portions of the image (tiles). The main idea is to divide the image into overlapping tiles and individually enhance each one of them. Enhanced tiles are then mosaicked back together using multi resolution spline technique [2]. The tile size is an important issue and should be comparable in size with the smallest object to be preserved locally. The minimum size for the tile is constrained by the use of multi resolution spline technique so that the image pyramid would still make sense. We use tiles of size 64x64 pixels.

The algorithm is divided into two steps. In the first step, the adjustment parameters are acquired for each tile, sliding the tile-size window over the image with some certain "step". This "step" parameter is defined a priori and controls the amount of overlap which is usually half or quarter of the tile size. In the case that step parameter is equal to 1, our approach becomes a pixel-by-pixel one [5]. To guard against possible noise and enforce smoothness it is suggested to refine the map of adjustment parameters using simple filters such as median, gaussian or thresholding.

In the second step we render the resultant image by adjusting all tiles and mosaicking consecutive tiles together. This process is done by rows where each row is constructed by consecutively blending neighboring tiles. In order to blend tiles we opt for multi-resolution spline technique [2] known to provide smooth blending yet preserving features located in

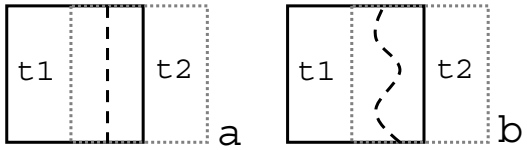

Fig. 3. Transition zones indicated by dashed lines (a) equidistant and (b) error minimization.

the overlapping area.

During the mosaicking procedure, the images to be blended are first decomposed into a multi-resolution laplacian pyramid (Fig. 2). Both pyramids are then spliced level by level, with each level being spliced using a weighted average over a transition zone. Then the blended image is obtained by reversely composing the spliced laplacian pyramid. Therefore the spline is matched to the scale of features and images are blended gradually without blurring finer image details.

The averaging transition zone can be easily defined as a line equidistant to borders of both tiles (Fig. 3(a)) represented by a dashed line. Another more sophisticated approach is to define the transition zone by minimizing the error in the overlapping area (Fig. 3(b)). The approximate solution to this minimization problem is recently given by a computationally efficient graph-cut algorithm [6]. We will define the graph where each node correspond to a pixel in the overlapping area between the two tiles $t1^{ov}$ and $t2^{ov}$. The weight of the edge (p,q), where p and q are adjacent nodes, is defined by a cost function $W(p,q)$ given by:

$$W(p,q) = \frac{\|E(p)\| + \|E(q)\| + Do(p)}{\|G_{t1}(p,q) + G_{t2}(p,q)\|}$$

Where the error is defined as $E(p) = t1^{ov}(p) - t2^{ov}(p)$, G is a gradient defined as: $G_t(p,q) = t^{ov}(p) - t^{ov}(q)$ and $D_o(p)$ is a minimum distance from pixel p to the overlap border. This cost function provides splicing that avoids high error areas, uniform areas, overlapping area borders and flows around high gradient areas. Source and sink links are also initialized for left-most and right-most border pixels of overlapping area.

4. CONTRAST ENHANCEMENT ALGORITHM

We will now demonstrate the use of the proposed framework for the local contrast enhancement (HDR compression) problem. The dynamic range of each tile needs to be preserved while minimizing the global dynamic range of the whole image. A straightforward approach is to stretch the histogram of each tile in order to fit it into the desired dynamic range. The adjustment parameter maps are then constructed by extracting max/min values for each tile. This simple solution has an important drawback that these max/min maps manifest a block-like nature. In fact, they essentially are outputs of dilation/erosion operators with kernel size equal to the tile size. This can represent problems over relatively uniform areas with high spikes. The tile incorporating a spike will not

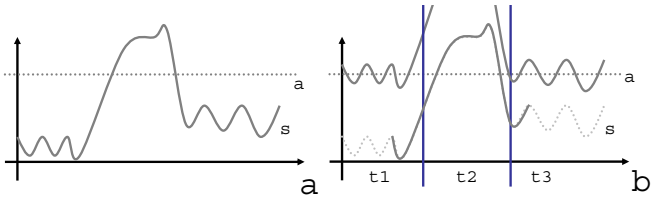

Fig. 4. Exemplar intensity profiles, (a) original and (b) adjusted for tiles t1, t2 and t3. Tiles t1 and t3 are enhanced although tile t2 remains the same.

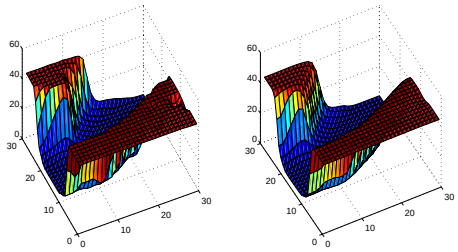

Fig. 5. Maps of adjustment parameters, original on the left and filtered (median and gaussian) on the right.

be adjusted similarly to its neighboring tiles and could lead to a different intensity patch in the resultant image.

To overcome this problem, we obtain the adjustment parameter for each tile using its average intensity, the amount of enhancement is then defined by the ratio of desired-average-intensity over the tile-average-intensity $adj_{tile} = \frac{avg_{des}}{avg_{tile}}$. The adjustment parameter map for the whole image is then constructed and each tile T is enhanced as follows:

$$T_{tile} = \begin{cases} T_{tile}, & \text{if } adj_{tile} > 1 \\ T_{tile} \cdot adj_{tile}, & \text{else} \end{cases}$$

To clarify this step the adjustment is demonstrated using the intensity profiles of the signal in Fig. 4. The curve marked as "s" represents a signal and dotted line "a" is a value of desired-average-intensity. The Fig. 4(b) shows that the signal contained in the tiles t1 and t3 is enhanced although tile t2 remains the same. Abrupt discontinuities in consecutive tiles left after the enhancement step are then removed by the multi-resolution spline technique. In order to filter out noise and obtain a smooth output image, we first up-threshold the adjustment parameter map by the values that could only be produced by tiles containing no information. Then, a median filter followed by a gaussian filter are applied to remove some imminent noise and enforce smoothness of adjustment parameter map. A not-processed and a processed adjustment parameter maps are shown in Fig. 5. These maps were generated to enhance the image in Fig. 8.

The desired-average-intensity parameter provides flexibility to tailor the method for a particular user's taste. Four possible values of this parameter are proposed: Low, Medium, High and Extra High. The "medium" value is defined as average intensity of the image. Other values are obtained from the sorted list of tile's average intensities. The "extra high" is the highest average intensity from this list. In our implementation "high" value is 30% below the highest average and "low" is 15% below the average position. Moreover, the use of tiles allow interactive adjustment of desired-average-intensity. In this case only the tiles with changed adjustment parameters are enhanced and mosaicked back into the final output.

There are two known drawbacks of the proposed algorithm. If objects are smaller than the tile size, they might not be enhanced optimally. Thus the choice of the tile size is of importance for optimal performance. Secondly, using equidistant transition zones to spline tiles may result in visible halos between two regions of highly different intensities.

5. EXAMPLES

The proposed algorithm's performance is demonstrated in following examples that show original and processed images. Confocal images of cat retina labeled with antibody to calretinin are shown in Fig. 6 (histogram equalized image is given for reference) and in Fig. 7. Cross-section stained with TOPRO is shown in Fig. 8. Fig. 9 shows fluorescent image of microtubules, enhancement is performed in original 12bits data and then linearly normalized into 8bits.

6. CONCLUSION

A tile-based contrast enhancement method is presented and its performance is demonstrated on different microscopy images. The authors carried out extensive experiments and obtained promising results for both computational efficiency and enhancement quality. **Acknowledgments:** Authors would like to thank Dr. Mark Verardo, Prof. Steven Fisher, Dr. Geoffrey Lewis, Prof. Stuart Feinstein, Kenneth Linberg, Austin Peck and Kallen Betts from Neuroscience Research Institute for generously providing image data.

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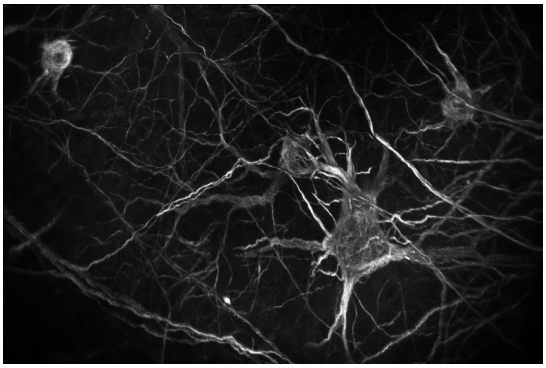
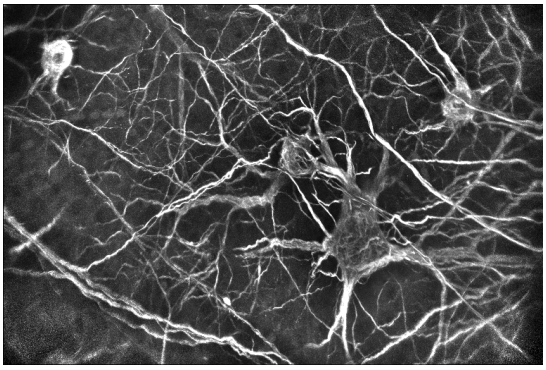
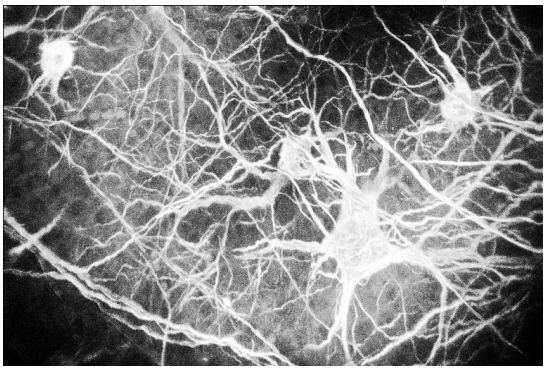


(a) Original image

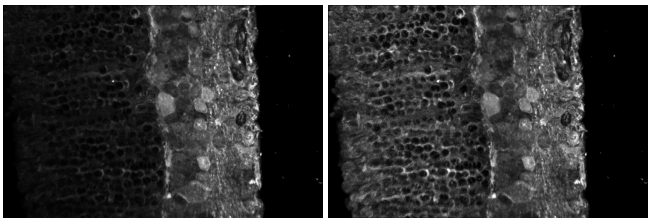


(b) Local enhancement



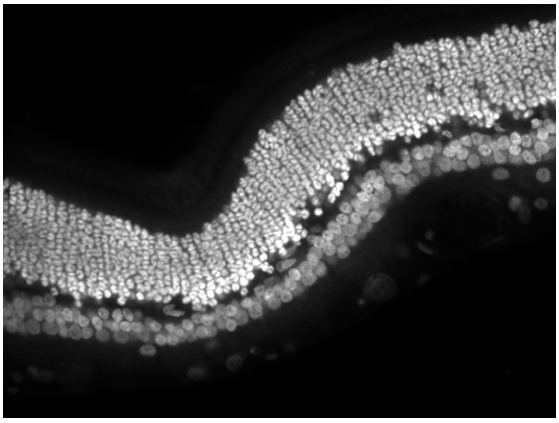
(c) Histogram equalization

Fig. 6. A laser scanning confocal image of a whole mounted 7day detached cat retina stained with an anti-neurofilament antibody. Ganglion cell bodies and their processes are labeled.

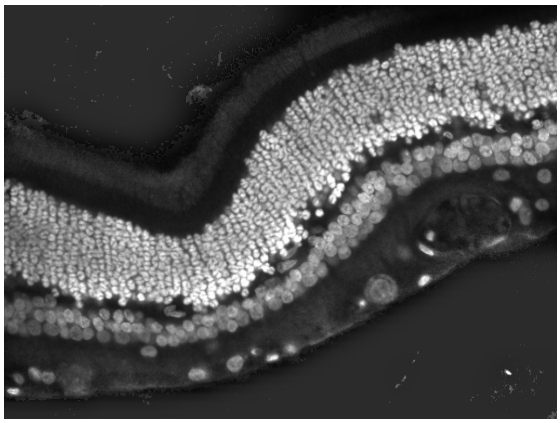


(a) Original image (b) Local enhancement

Fig. 7. Confocal image of cross-section cat retina labeled with antibody to calretinin.

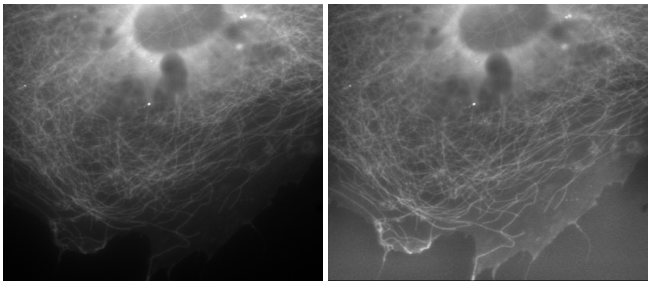


(a) Original image



(b) Local enhancement

Fig. 8. A single plane image from a laser scanning confocal microscope of a 3 day detached cat retina section stained with TOPRO, a nuclear dye.



(a) Original image (b) Local enhancement

Fig. 9. Fluorescent image of microtubules.