MOSAICKING BASED FRAMEWORK FOR LOCAL ENHANCEMENT OF BIO IMAGERY

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ABSTRACT

We propose an algorithm to process images using their local information. Each image is tiled with overlapping neighborhoods. Then, each region is enhancement independently. The overlapping tiles are then seamlessly mosaicked to construct the multi-focus image. Our approach is presented for images from optical and fluorescent microscopy and demonstrates better local contrast preservation in comparison with traditional global approaches (histogram stretching or equalization).

1. INTRODUCTION

tilde ~ tilde The dynamic range of modern systems employed for bio-medical 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. 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 saturation. 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. The input image is divided into small overlapping tiles and then each tile is individually enhanced. Tiles are then seamlessly mosaicked back together using multi resolution spline (MRS) technique [2]. Our approach is robust to acquisition parameters and temporal changes. Since we blend the images using pixel data from the spatial domain (as opposed to fusing the information in a transform domain), the resulting images have fewer artifacts. Moreover, our framework allows to solve different problems, such as: dynamic range compression, uneven illumination correction [3], multi-focus [4] and multi-exposure imaging.

This paper is structured as follows: first we give an overview of previous research in section The the description of the tile-based framework is presented in section

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2. TILE-BASED FRAMEWORK

In this section the framework for image processing using local information is presented. The input image is divided into small overlapping tiles and then each tile is individually enhanced. Tiles are then seamlessly mosaicked back together using multi resolution spline (MRS) 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 MRS so that the image pyramid would still make sense.

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 of the tile size. Obtained parameter matrices we will call as adjustment maps. To guard against possible noise and enforce smoothness the maps are refined using filters such as median and gaussian.

In the second step, we render the resultant image by 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 the overlapping area. During this procedure, the images to be blended are first decomposed into a multi-resolution laplacian pyramid. The 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. To improve speed using more memory the whole process can be done at once by assembling laplacians for the whole row or image and then reversing the whole structure.

The averaging transition zone can be easily defined as a line equidistant to borders of both tiles. The more elegant solution is to minimize the negative effect of the tile size with objects of curved structure by defining the transition zone between tiles as an error minimization problem. The error surface is defined in the overlapping area between tiles. The approximate solution to this minimization problem is recently given by a computationally efficient graph-cut algorithm [5]. 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.

3. IMAGE ENHANCEMENT ALGORITHM

We will now demonstrate the use of the proposed framework for uneven staining correction of confocal images. We would like to obtain the image with the same average intensity and standard deviation over all local regions. Therefore each tile I_t is normalized using desired-average-intensity and desired-standard-deviation μ_d, σ_d, respectively.

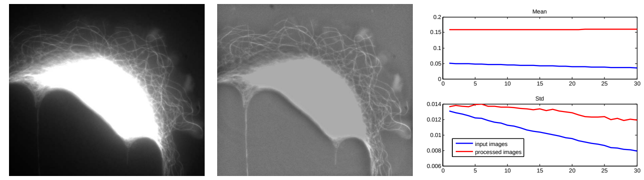
$$I_t^{'} = \begin{cases} (I_t - \mu_t) + \mu_d, & \text{if } (\sigma_t > \sigma_d) \\ (I_t - \mu_t) \cdot (\sigma_d/\sigma_t) + \mu_d, & \text{else} \end{cases}$$

Values μ_t and σ_t are computed for each tile and define adjustment maps. In this case there are two maps, first created from means and the second from ratios of standard deviations σ_d/σ_t. In order to avoid spurious results due to spikes of noise the value of σ_t is robustly obtained using Median Absolute Deviation (MAD). In order to remove some imminent noise and enforce smoothness we filter adjustment parameter maps before processing tiles.

There are two known drawbacks in 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, if equidistant transition zones are used to mosaic tiles the result may contain visible halos between regions of highly different intensities.

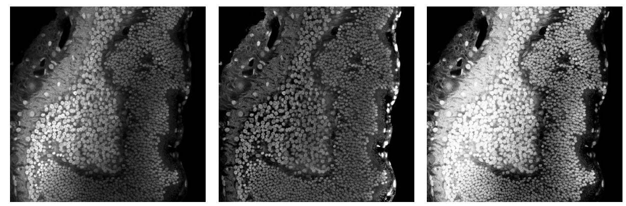
4. EXPERIMENTAL RESULTS

The performance of our algorithm was tested on several examples and the results were submitted to feature extraction and object detection that demonstrated improved precision. Tile sizes in the range of 16 and up to 64 pixels were used in our experiments. Fig. 1 shows results for a stack of 30 fluorescent images of microtubules enhanced both in space and time, enhancement is performed in original 12bits. Means and standard deviations for all 30 frames are presented in (c). It is



(a) Original image (b) Local enhancement (c) Stack statistics

Fig. 1. Time stack of 30 fluorescent images of microtubules. The photo-bleaching effect responsible for gradual fluorescence decay was corrected for the entire stack.



(a) Original image (b) Local enhancement (c) Histogram equalization

Fig. 2. One plane of a 3D image from laser scanning confocal microscope of a 7 day detached cat retina section stained with TOPRO, a nuclear dye.

visible that the photo-bleaching effect responsible for gradual fluorescence decay was corrected for the entire stack. Cross-section of a 7 day detached cat retina stained with a nuclear dye TOPRO acquired by laser scanning confocal microscope is shown in Fig. 2.

5. CONCLUSION

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.

6. REFERENCES

[1] R. Fattal, D. Lischinski, and M. Werman, "Gradient domain high dynamic range compression," in *SIGGRAPH, Comp. Graph. Proc.*, 2002, pp. 249–256.

[2] P. J. Burt and E. H. Adelson, "A multiresolution spline with application to image mosaics," *ACM Transactions on Graphics*, vol. 2, no. 4, pp. 217–236, 1983.

[3] B. S. Manjunath, B. Sumengen, Z. Bi, J. Byun, M. El-Saban, D. Fedorov, and N. Vu, "Towards automated bioimage analysis: From features to semantics," in *IEEE Int. Symposium on Biomedical Imaging (ISBI)*, 2006.

[4] Dmitry Fedorov, Baris Sumengen, and B. S. Manjunath, "Multi-focus imaging using local focus estimation and mosaicking," in *IEEE International Conference on Image Processing 2006 (ICIP06)*, Oct 2006.

[5] Yuri Boykov and Vladimir Kolmogorov, "An experimental comparison of min-cut/max-flow algorithms for energy minimization in vision," in *Energy Minimization Methods in Computer Vision and Pattern Recognition*, 2001, pp. 359–374.