



RESOLUTION ENHANCEMENT FOR COLOR TWEAK IN IMAGE MOSAICKING SOLICITATIONS

Ms.P.Narayani alias Meena², Ms.S.Ushanandhini³, Ms.K.Vinothini⁴, Ms.G.Annalakshmi¹

Dept. of ECE, Alpha college of Engineering and Technology, Pondicherry, India.

shalinigajendran@pec.edu¹, meena9095@gmail.com², sivanandhini42@gmail.com³,

vinothinikannan26@gmail.com⁴

Abstract: Image mosaicking have found a vast field of applications ranging from satellite or aerial imagery to medical imaging street view maps, city 3D modelling, texture synthesis or stereo reconstruction and so on. It is an attempt to enhance the prospect approach for color correction in mosaic images. A region of mosaic can be viewed at a resolution higher than any of the original frames. Geometrical and Photometrical registrations are the two problems in computing the mosaic image. The image to be color corrected is segmented into several regions using mean shift algorithm. The color correction is performed using the degree of resolution enhancement, which is determined using local joint image histograms. A maximum likelihood solution used in existing method takes an account of errors in the estimated homographies. A new color correction algorithm with the usage of truncated Gaussians is used to perform accurate color distribution. Color correction between two coarsely geometrically registered images involves the problem of adjusting the color palette of two images. Results of super resolution enhancement and an improved map estimator develop to regularize the sampling density of the scene and accurate alignment of the image.

Index Terms-color correction, image mosaicking, super resolution.

I. INTRODUCTION

Registration and mosaicking of images have been in practice long before the age of digital computers. After the development of airplane technology, aero photography became an exciting new field. The limited flying heights of the early airplanes and the need for large photo-maps, forced imaging experts to construct mosaic images from overlapping photographs. This was initially done by manually mosaicking images which were attained by rectified equipment. The need for mosaicking continued to increase later in satellite communication. Developments in computer technology became a natural enthusiasm to improve computational techniques and to solve related problems. The construction of mosaicking images and the use of such images on several computer vision/graphics applications have been

vigorous in areas of research. Mosaicking images on smooth surfaces permits an unlimited resolution in avoiding discontinuities that can result from images that are acquired separately. This information provides the users a presence of enhanced sense in a virtual scene. Environment computer vision methods can be used to produce intermediate nodes. As a reverse problem, the 3D structure of scenes can be restored from multiple nodes. A design proposed in the base paper [1] deals with augmenting the prospect approach for correcting photometrical disparities in mosaic images. The image to be color corrected is segmented into several regions using mean shift algorithm. Then, connected regions are extracted using region fusion algorithm and color correction is performed in these regions. This obtains the most robust results for color correction. In [4], although there are several methods dealing with color correction, a single step multi-dimensional probabilistic segmentation of three color channel of an image is determined. This 3D color space segmentation reduces the processing time over color correction algorithm. The approach used in [2] is Expectation-Maximization (EM) method which has two advantages like proposing both spatial and color smoothness or Gaussian components. Hence, natural color transitions are achieved among different regions of the image. The modeless approach used in [7] is the estimation of global and local color replacement function with help of tensor voting method. This results in image intensity compensation and high contrast image correction. The sequential method for estimating radiometric response, exposure functions and vignetting is described in [8]. To the best of our knowledge the proposed method describes a new color correction algorithm with high resolution mosaic image. Christo Ananth et al. [3] discussed about efficient content-based medical image retrieval, dignified according to the Patterns for Next generation Database systems (PANDA) framework for pattern representation and management. The proposed scheme use 2-D



Wavelet Transform that involves block-based low-level feature extraction from images. An expectation-maximization algorithm is used to cluster the feature space to form higher level, semantically meaningful patterns. Then, the 2-component property of PANDA is exploited: the similarity between two clusters is estimated as a function of the similarity of both their structures and the measure components. Experiments were performed on a large set of reference radiographic images, using different kinds of features to encode the low-level image content. Through this experimentation, it is shown that the proposed scheme can be efficiently and effectively applied for medical image retrieval from large databases, providing unsupervised semantic interpretation of the results, which can be further extended by knowledge representation methodologies.

II. PROBLEM FORMULATION

The major problem in the image can be corrected by color correction. In other words, color correction is the problem of adjusting the color palette of an image. Once the source and the target images have been segmented into the non-zero regions and the corresponding color transfer functions for each match are computed, the objective at this last stage is to correct the color of every single pixel. Because of the probabilistic nature of the proposed color segmentation, pixels may have non zero probability of belonging to more than one region. Hence, the proposed color transfer approach is defined as a weighted combination of all the computed color transfer functions. Let us consider the two images of the same scene. These two images are the source and target image which combines to form a mosaic image. The source and target images have the average pixels. The color can be corrected in target images. The image fusion is a process of joining two or more images to form another image by using some other algorithm. A pixel is the only basic unit of information with the pictures. The mean shift segmentation is more suitable for segmenting of high resolution pictures. The segmented regions should be matched. The color palette mapping functions should be similar to an ideal mapping functions in most cases of images. The comparison is only possible in the overlapping regions of images. There are several algorithms dealing with color tweaking which involves the strong assumptions. Then compare the tweaked picture into the source picture. This comparison is done in the overlapped regions of the picture.

III. PROPOSED APPROACH

The current paper proposes a resolution enhancement for color tweak in mosaicking images for the mapping functions. The overlapped portion of the target picture involves the mean shift algorithm which is segmented into several regions using the fusion algorithm and then fits with the MAP estimator (Maximum a posterior) method. This step is used to regularize the pictures. The final color tweaked image is formed by using color mapping function to the target image.

IV. IMAGE MOSAICKING PROGRESSION

Image mosaicking applications includes aerial imagery, satellite imagery, remote sensing, astronomy, ophthalmology and so on. The process of image mosaicking involves mean-shift segmentation, region fusion and color transfer. As these processes are done, the final mosaic image will be formed.

A. MEAN-SHIFT SEGMENTATION AND REGION FUSION

Mean-shift analysis is a newly developed non-parametric clustering technique based on density estimation for the analysis of complex feature spaces. It has found many successful applications such as image segmentation tracking and image fusion and so on. This method is used to do perform color segmentation of the overlapped portion of the target picture into the several regions. The target picture which contains the details of the source picture can be split into many regions. The mean shift method is used to refer the local color correction. The local color correction method is chosen because it is more advantageous than the global color correction. Mean shift algorithm is one of the steps used for color segmentation. Here, the EM segmentation can be used in both the source and target pictures. For each data points, it convergences as it is an advanced technique for the grouping based technology. The most significant application of the mean shift is clustering. It is a powerful unsupervised data analysis technique which does not require prior knowledge about the number of clusters and does not retains the shape of the clusters.

B. COLOR TRANSFER FUNCTIONS

The color transfer function reveals the source and target images which are segmented into several NG groups for representing the Gaussian mode. It is necessary to form a each Gaussian component from the target image to an another

source image, in which the images are registered. This also performs the correlation of the pixels.

$$m(k) = \arg\max(r(k, j)), \forall j \{1, 2, 3, \dots, N G\} \quad (1)$$

here, $m(k)$ represents the matching function from the source image component for the target images of component k .

i) LOCAL COLOR CORRECTION

Assume the 8-bits RGB color images from the range of (0 to 255). These algorithm can be done in two steps. They are,

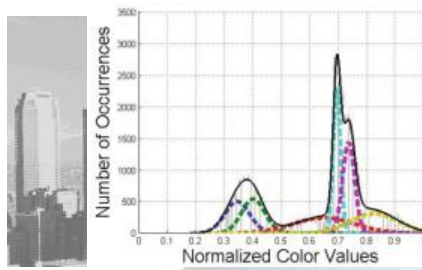


Fig.1(a)

Fig.1(b)

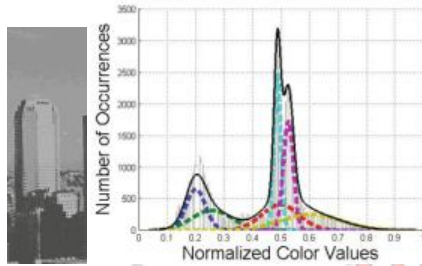


Fig.2(a)

Fig.2(b)

Fig.1(a) source image Fig.1(b) Gaussian mass of the source image Fig.2(a) Target image Fig.2(b) Gaussian mass of the target image.

1. A mask image is getting by the input image.
2. The input and mask image are combined to get the result.

The mask image is obtained by inverting and blurring the intensity component of the input image is given by

$$M(x, y) = (\text{Gaussians} * (255 - I(x, y))) \quad (2)$$

Blurring is performed by the Gaussian kernel of the image contrast which can be reduced along the edges.

ii) GLOBAL COLOR CORRECTION

In image processing, color balance of an image is the global adjustment of color intensity that enhances the whole photograph. Once the global correction is done, we move to the local correction for some selected areas in our picture. This approach at least shows 80% of the pixels

in color correction. The global correction is used to correct any region of the picture or any part of the picture. The purpose of global correction is to improve the contrast, mid-tone brightness and color balance. The global enhancement provides the foundation to build the great pictures.

C. LOCAL JOINT IMAGE HISTOGRAM

The target image can be split into several regions. The joint image histogram is employed for color correction solicitations. The image histograms are also one of the global correction method. Let x and y be the random variables and the cell index (x, y) be the value of x is which is mapped into the value of y . Here, X and Y are the discrete random variables that contain all the values of the color in source and target images. The equation for the joint image histogram is given by,

$$I^j(x, y) = \frac{\sum_{u=0}^{W-1} \sum_{v=0}^{H-1} \delta(T_p^j(u, v), x) \cdot \delta(S_p^j(u, v), y)}{W \cdot H} \quad (3)$$

Where (u, v) are the coordinates of the pixel, W and H are the width and height of the images, $\delta(\cdot)$ is the kronecker delta function.

D. COLOR PALETTE MAPPING FUNCTIONS

We propose an approach for color correction using color palette mapping functions with respect to color segmented regions in the overlapped part of the target image. The process is very simple in which each pixel can be corrected using the color palette mapping functions that match the region to the pixel being in the right place. In case of correcting full target image, it is a complicated task since all the pixels in the target image are identified as color segmented regions.

Let the solution for the above problem considered for each pixel in target image T is to compute j of the corresponding region and then match with T^j region. This problem can be reduced by matching every region. Let \bar{X}^j be the vector of average color in the segmented region of three channels of the target image T . The average color of the image T_p is \bar{X}_p^j . Then, the equation can be given as

$$\text{map}(j) = \arg\min(E(\bar{X}^j, \bar{X}_p^j)), i \quad (4)$$

E. GEOMETRICAL TRANSFORMATIONS

The geometrical transformations change the spatial relationship between the objects of the picture. One of the principle applications of geometric transformations shows the possibility of tweaking

the digital images of the distortions introduced by the camera. Often the images produced by inexpensive cameras present geometric distortions in very large nature. These images must be tweaked in order to use metrically. Let us consider a homographic planar projective transformation. This is illustrated in figure for two situations:

- images of a plane from different camera positions and
- Images of a scene from a panning. The point's x and x' correspond to actual point X in original scenes.

F. PHOTOMETRICAL REGISTRATIONS

Along with geometric transformations, there should occur some photometric changes in the images. Photometric registration deals with estimation of photometric alignment of captured image due to changes in illumination, intensity etc. A simple parametric model of these effects can be used and the parameters can then be estimated using the available images. Figure 3 shows an example using a model that allows for an affine transformation (contrast and brightness) per RGB channel.

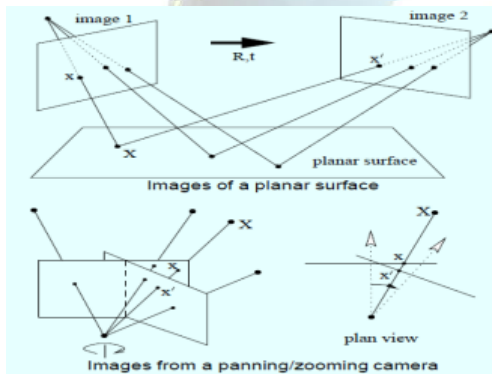


Fig. 3

Fig. 3 shows the geometric transformations of the planar surfaces.

G. SUPER RESOLUTION

Super-resolution is based on the idea that the combination of low resolution (noisy) sequence of images of a scene can be used to generate a high resolution image or image sequence. Thus it attempts to reconstruct the original scene of image with high resolution given in a set of observed images at lower resolution. The general approach is considering the low resolution images as resulting from re-sampling of a high resolution image. The goal is to recover a high resolution image when re-sampling based on the input images. The

imaging model will produce low resolution of observed images. Thus the accuracy of imaging model is vital for super-resolution and an incorrect modelling, say of motion, can actually degrade the image further. The observed images could be taken from one or multiple cameras or could be frames of a video sequence. These images need to be mapped to a common reference frame. This process is registration. The super-resolution procedure can then be applied to a region of interest in the aligned composite image. The key for successful super-resolution consists of accurate alignment, i.e. registration and formulation of an appropriate forward imaging model. The figure given below shows the stages in super-resolution process.

H. MAP ESTIMATOR

Sometimes we have prior information about the physical process whose parameters are to be estimated. Such information can come from the empirical evidences and also the already estimated physical information. This information can be encoded by the probability density functions on which the parameter exists and the parameters are

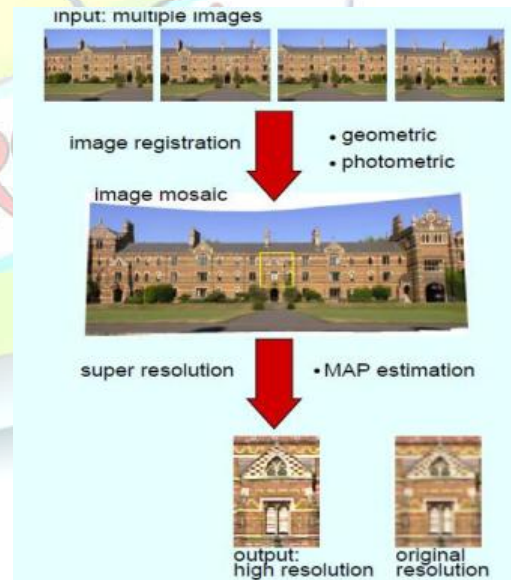


Fig. 4 shows the performance of super resolution algorithm in mosaic image

represented by $p(\frac{\theta}{x})$. Then the prior probabilities are represented as $P(\theta)$. The priors are called as Bayesian interference. The bayes theorem shows the information in the process of estimation.

$$P(\theta/X) = \frac{P(X|\theta)P(\theta)}{P(X)} \quad (5)$$

The term on the left side is posterior and the right side shows likelihood prior term and the denominator shows normalization to change the term into unity. Thus, Bayesian inference evolves the maximum a posterior (MAP) estimate.

$$\text{argmax} P(\theta/x) = \text{argmax} P(x/\theta)P(\theta) \quad (6)$$

V. RESULTS

Here we suggested for performing local color transfer automatically and maintaining color and spatial coherence. We recommended probabilistic segmentation and model these regions as Gaussian Mixtures. A modified EM algorithm is also introduced by augmenting a smoothness propagation step to enforce spatial and color consistency among regions or Gaussian components. Our unified model is general and can be applied to a wide range of applications including deblurring, image restoration and colorization of images. In our upcoming work, we will investigate spatially coherent texture transfer and video transfer. We have enhanced super resolution image with the help of MAP estimator for the accurate alignment. This methodology obtain the EXPERIMENTAL OUTCOME

better results compared to other techniques. Thus the outcome suggests that the parametric methods are more efficient than other techniques for image color correction.

VI. CONCLUSION

Our paper proposes a color correction algorithm for mosaic image with high resolution. The process deals with multiple images which are segmented into several regions using mean shift and connected regions are extracted using fusion algorithm. It is necessary to compute local color mapping function to each region of an image and its results were obtained using gaussian distributions. Finally, the color palette mapping is applied to whole functions in the images and it can be able to produce an mosaic image where there is no color transitions. The above results are shown for the mosaic images as well as the local joint image histogram which also improve the effectiveness of color correction performance in it.



Fig 5 (a)



Fig 5 (b)



Fig 5 (c)



Fig 5 (d)



Fig 5(e)

Fig 5 (a) shows source image and (b) shows target image (c) It shows the mean shift segmented (d) shows the region fusion (e) shows the mosaic image



REFERENCES

- [1] Miguel Oliveira and Angel Domingo Sappa, "A probabilistic approach for color correction in image mosaicking application," *IEEE Trans.* vol. 24, no.2, pp.508-523, Feb.2015.
- [2] Y.W.Tai, J.Jia, and C.K.Tang, "Local color transfer via probabilistic segmentation by expectation-maximization," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun.2005, pp.747-754.
- [3] Christo Ananth, K.Kalaiselvi, C.Kavya, S.Selvakani, P.Sorimuthu Iyan, "Patterns for Next generation Database Systems - A study", *International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)*, Volume 2, Issue 4, April 2016, pp: 114-119
- [4] M.Oliveira, A. D.Sappa, and V. Santos, "Color correction using 3D Gaussian mixture models," in *Proc. ICIAR*, Jun. 2012, pp.97-106.
- [5] M.Oliveira, A.D.Sappa, and V.Santos, "Unsupervised local color correction for coarsely registered images," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun.2011, pp.201-208
- [6] B.Zitová and J.Flusser, "Image registration methods: A survey," *Image Vis. Comput.*, vol.21, no.11, pp.977-1000, Aug.2003.
- [7] J.Jia and C.-K.Tang, "Tensor voting for image correction by global and local intensity alignment," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol.27, no.1, pp.36-50, Jan.2005
- [8] S. J.Kim and M. Pollefeys, "Robust radiometric calibration and vignetting correction," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol.30, no.4, pp.562-576, Apr.2008.
- [9] X. Zhang and B.A. Wandell, "A spatial extension of CIE LAB for digital color-image reproduction," *J.Soc. Inf. Display*, vol. 5, no.1, pp.61-63, Mar.1997
- [10] F.Pitie, A.C.Kokaram, and R.Dahyot, "Automated colour grading using colour distribution transfer," *Comput. Vis. Image Understand.*, vol.107, nos.1-2, pp.123-137, Jul.2007.
- [11] D.Comaniciu and P.Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol.24, no.5, pp.603-619, May 2002
- [12] M.Ben-Ezra, A.Zomet, and S.Nayar, "Video super-resolution using controlled subpixel detector shifts," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol.27, no.6, pp.977-987, Jun.2005.
- [13] A.Abadpour and S.Kasaei, "A fast and efficient fuzzy color transfer method," in *Proc. 4th IEEE Int. Symp. Signal Process. Inf. Technol.*, Dec.2004, pp.491-494.