In 17th Portuguese Conference on Pattern Recognition (RecPad 2011)
Porto, Portugal, October 2011

Enforcing Consistency of Image Gains in Panoramic Mosaics

Ricardo Galego
Ricardo Ferreira
Alexandre Bernardino
José Gaspar
{rgalego,ricardo,alex,jag}@isr.ist.utl.pt

Instituto de Sistemas e Robótica
Instituto Superior Técnico
Lisboa, Portugal

Abstract

In this paper we propose a methodology for normalizing the images gains in a mosaicked representation of a scene imaged by a pan-tilt camera. The normalization is based on assuming that one image has unit gain and then estimating, and filtering, the relative gains of all the other images, using the known geometry of the pan and tilt camera to find corresponding points (color values). Experiments with real images show that a mosaic built with image gains normalization has lesser visible seams at the borders of image stitching.

1 Introduction

In many computer vision systems the image intensity is considered to be proportional to the scene radiance. This is not true in general, due to various factors such as lesser optical gain while moving away of the optical axis (vignetting), the electronic or chemical photo-detector conversion of the image brightness into image irradiance [4] or the radiometric response function of the camera [2, 3, 5, 6]. Without calibrating the color information, which is distorted by camera system components, the results of brightness intensity image analysis may conceal or inaccurately represent important intensities characteristics of objects in images. In other words, applications requiring the true colors of the objects, such as comparing images of objects acquired with different settings, imply correcting the non-linear radiometric mapping into a linear one by calibrating the radiometric response of the camera system.

2 Image Formation

The energy (irradiance) observed by the CCD is not the same energy emitted by the object (source). This is due to lens induced non uniform transmittance function known as vignetting that causes a fade-out in the image periphery. The vignetting is a gain on the image brightness that is normalized to one in the center and deceases towards the borders. The energy observed, E, by the camera at the pixel $[u,v]$ is a function of the object radiance, R_X and the gain induced by vignetting $V(u,v)$. Where R is the radiance emitted by the object at the position of the world X and the V is the gain at the position u and v of the image. The energy observed is:

$$E_{(u,v)} = V(u,v)R_X \tag{1}$$

Additionally the time that the energy is observed (shutter time duration) can be represented as a gain on the energy, k, resulting:

$$E_{(u,v)} = kV(u,v)R_X \tag{2}$$

The function, f that converts irradiance to image brightness is called radiometric response function (RRF). The function is non-linear and it is usually induced by manufacturers intentionally to fit a wider dynamic range of brightness. Making the pixel intensity on an image a function of the radiance emitted by the object, the vignetting caused by lens and the RRF induced by the manufacturers:

$$I_{(u,v)} = f(kV(u,v)R_X) \tag{3}$$

3 Finding Consistent Gains

Nowadays cameras are automatic and adapt to the environment, making darker or brighter images, so the user sees more clearly the pictured scene. This adaptation can be done by several mechanisms. The most common adaptation mechanisms are changing the iris aperture or the shutter time duration. This feature is appreciated by most of the users, however for

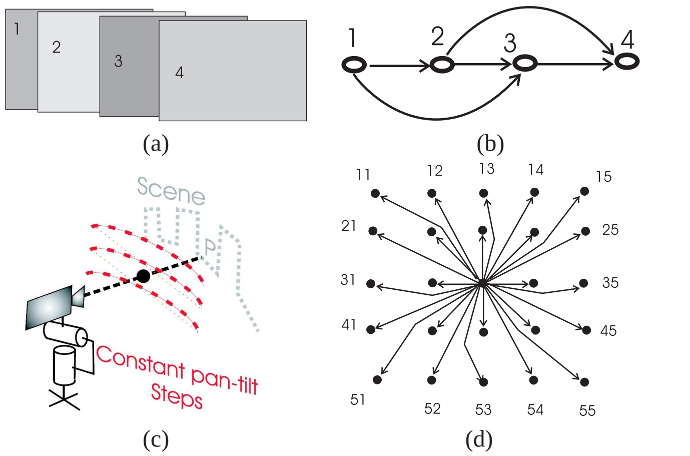


Figure 1: A panoramic sequence of images (a) and the graph corresponding to the sequence (b). Acquisition of grid of images, considering constant pan-tilt steps (c). A graph representing the grid of images (d). Circles denote images and arrows (links) denote gains between images. In (d) we show only the links between the central image and all its neighbors.

surveillance, where a database is needed this feature brings a new challenge, which is the need of normalizing the exposure of all the images, since one wants to observe all the images captured with the same settings.

If we observe a sequence of images, for instance captured with a constant step of pan and tilt having overlap between the images acquired, one can observe different global intensities of the images along the set captured (see Fig 2 (a) the mosaic of the images). In order to normalize these differences firstly we compute the gains between all pairs of overlapping images. If we invert the radiometric response function, the gain between each pair of images is computed from a set of pixels imaging the same objects and that are at the same distances from the optical center of the image. Enforcing equal distances for corresponding pixels is necessary to avoid errors related with the vignetting, $V(u,v)$. For example considering two images, I_i and I_j, in the overlapping region, at corresponding points, at the same distance of the center, one has

$$g(I_i) = k_i VR \quad \wedge \quad g(I_j) = k_j VR. \tag{4}$$

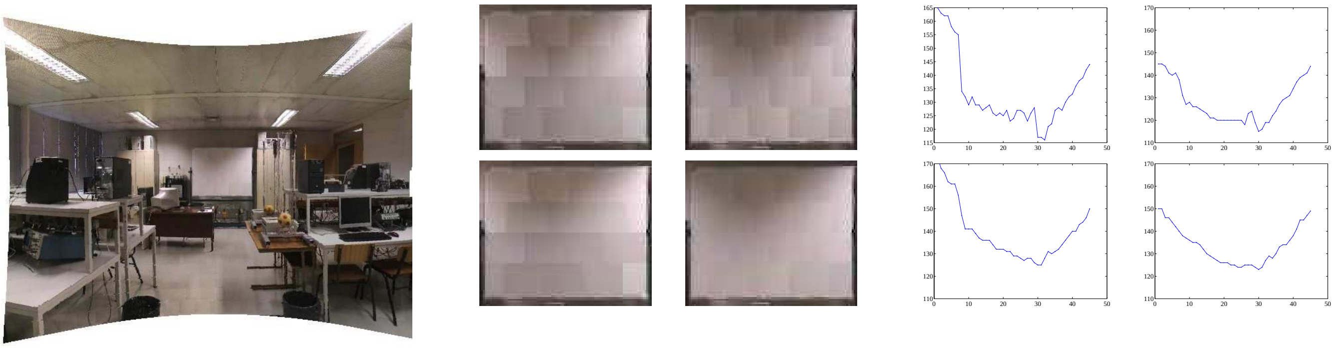
where g is the inverse function of the radiometric response function. Assuming an affine model between the two images, one has:

$$g(I_j) = \alpha_{ij} g(I_i) + \beta_{ij} \tag{5}$$

where α_{ij} represents scaling between the image i and j, and β_{ij} an offset[1]. Considering that every image has some overlapping with at least one other, and do not form disconnected subsets, it is possible to compute the gains among all images. The gain associated to each pair of images work as a link between the images. Figure 1 shows the graph created by the sequence of four images, where the first have overlap with the second and third but not with the fourth.

With the gains and the images it is possible to make a graph, where the nodes are the globally consistent image values, G_j and the gains between images are the links, as it is shown in Fig. 1. The gain in each pair of images is considered to be an affine transformation as Eq. 5 shows. This gain is computed using RANSAC to exclude outliers. Equation 6 shows that is possible to compute the value of the G_n if we know the value of the node, G_i , and the links (gains) that we need to pass through to get to the

[1]Despite considering affine transformations of brightness between the images, we still term the relations of brightness as gains, since the solution we propose works also for simple gains (linear relations), and the explanation is more clear using just gains.



(a) (b) (c)

Figure 2: (a) Final result of a mosaic after correcting the vignetting and normalized the image gains. (b) Zooms of mosaics built with, or without, vignetting and image gains normalization. From left to right and up to down, lacking of both vignetting-correction and image gains normalization, having image gains normalization and lacking vignetting-correction, with vignetting-correction and lacking of image gains normalization and the last one with vignetting-correction and image gains normalization. (c) profiles from a horizontal line of the images in (b).

node G_n:

$$G_n = \alpha_{jn}G_j + \beta_{jn} = \alpha_{jn}\alpha_{ij}G_i + \alpha_{jn}\beta_{ij} + \beta_{jn}. \tag{6}$$

A way to normalize the gains linking all images is to form a system of equations collecting all the observed gains, a subset of the all the 2-combinations of the total set of images. In other words, one forms a system of equations $A\mathbf{x} = \mathbf{b}$ collecting together all the equations Eq.5 formed with all the estimated α_{ij} and β_{ij}, factorizing the node values $\mathbf{x} = [G_1\ G_2 \ldots G_n]^T$:

$$\begin{bmatrix} 1 & 0 & 0 & \ldots & 0 \\ -\alpha_{12} & 1 & 0 & \ldots & 0 \\ 0 & -\alpha_{23} & 1 & \ldots & 0 \\ -\alpha_{13} & 0 & 1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ -\alpha_{1n} & 0 & 0 & \ldots & 1 \end{bmatrix} \begin{bmatrix} G_1 \\ G_2 \\ G_3 \\ \vdots \\ G_N \end{bmatrix} = \begin{bmatrix} C \\ \beta_{12} \\ \beta_{23} \\ \beta_{13} \\ \vdots \\ \beta_{1N} \end{bmatrix} \tag{7}$$

The size of the matrix A is $M \times N$, where N is the number of images and M is the number of links in the graph, $\mathbf{b}$ is a vector $N \times 1$. We can obtain therefore a least squares solution with $\mathbf{x} = (A^TA)^{-1}A^T\mathbf{b}$, assuming that the graph is a connected graph.

In the case one chooses a pure gain model, i.e. assuming $\beta_{ij} = 0$, then it is possible to estimate consistent gains $\hat{\alpha}_{ij}$ by solving Eq.7, considering without loss of generality $C = 1$. Having found the G_i, one obtains $\hat{\alpha}_{ij} = G_j/G_i$.

Considering the affine model, as proposed in Eq.5, one can estimate consistent values for $\hat{\alpha}_{ij}$ and $\hat{\beta}_{ij}$ simply by solving Eq. 7 for two different values of C. In this work we use $C = 1$ and $C = 2$, resulting in two solutions for G_i. We term the solutions G_{min} and G_{max} for $C = 1$ and $C = 2$, respectively. With these two solutions we can recalculate the parameters solving the next 2×2 matrix equation:

$$\begin{bmatrix} G_{imin} & 1 \\ G_{imax} & 1 \end{bmatrix} \begin{bmatrix} \hat{\alpha}_{ij} \\ \hat{\beta}_{ij} \end{bmatrix} = \begin{bmatrix} G_{jmin} \\ G_{jmax} \end{bmatrix}. \tag{8}$$

4 Normalizing the Image Gains

Having estimated consistent $\hat{\alpha}$ and $\hat{\beta}$ values, using Eq.8, we can normalize all the images to be gain-consistent with a reference image h:

$$\hat{I}_i = f(\hat{\alpha}_{ih}g(I_i) + \hat{\beta}_{ih}) \tag{9}$$

where $\hat{I}_i$ denotes the gain normalized image obtained from the (original) I_i.

Finally, in order to obtain even lesser visible seams (artifacts) while stitching images to form the mosaic, one needs to, additionally, correct image vignetting. We correct the vignetting using the correction model and algorithm in [1].

5 Experiments

In our experiments we used a Sony EVI D30 to scan a room and create four background representations: (i) lacking both the image gains normalization and vignetting-correction, (ii) lacking image gains normalization but including vignetting-correction, (iii) having image gains normalization but lacking vignetting-correction, and (iv) having both image gains normalization and vignetting-correction (see Fig. 2). The gain and iris are fixed, but the shutter time is left free to be adjusted automatically by the camera.

Figure 2(b) shows zoomed parts of the global mosaic, namely the white board. Figure 2(c) shows horizontal profiles of about half width of the zoomed mosaics. Both in (b) and (c) top-left, top-right, bottom-left and bottom-right correspond respectively to the cases (i) to (iv).

The artifacts due to the automatic shutter time, namely the nonuniform appearance of the white board which appear to be split into several patches with different gray scales, are less visible when normalizing the image gains or correcting the vignetting. As expected, the artifacts are even lesser visible when we applied both the normalization of the image gains and vignetting correction.

6 Final notes and future work

In this paper we proposed normalizing the image gains method for pan-tilt cameras. Experiments have shown that the normalization allows building (mosaicked) scene representations having less variance and therefore more effective for event detection. Future work will focus on maintaining minimized variance representations accompanying the daylight change.

7 Acknowledgments

This work has been partially supported by the Portuguese Government - Fundação para a Ciência e Tecnologia (ISR/IST pluriannual funding) through the PIDDAC program funds and through the project DCCAL, PTDC / EEACRO / 105413 / 2008.

References

[1] R. Galego, A. Bernardino, and J. Gaspar. Vignetting correction for pan-tilt surveillance cameras. In *VISAPP*, 2011.

[2] D.B. Goldman. Vignette and exposure calibration and compensation. *IEEE T-PAMI*, 32(12):2276 –2288, 2010.

[3] M.D. Grossberg and S.K. Nayar. What is the space of camera response functions? In *IEEE CVPR*, volume II, pages 602–609, 2003.

[4] Sing Bing Kang and Richard S. Weiss. Can we calibrate a camera using an image of a flat, textureless lambertian surface? In *ECCV (2)*, pages 640–653, 2000.

[5] S. J. Kim and M. Pollefeys. Robust radiometric calibration and vignetting correction. *IEEE T-PAMI*, 30(4):562 –576, 2008.

[6] A. Litvinov and Y.Y. Schechner. Radiometric framework for image mosaicking. *J Opt Soc Am A Opt Image Sci Vis*, 22(5):839–48, 2005.