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Minimizing Seam Artifacts in Image Stitching

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Abstract: A specialized form of image mosaicing known as image stitching has become increasingly common, especially in the making of panoramic images. The stitching quality is measured visually by the similarity of the stitched image to each of the input images and by the visibility of the seam between the stitched images. In order to define and get the best possible stitching, first of all noise is removed from the input images which is done as a preprocessing step and also there are several formal cost functions for the evaluation of the stitching quality. In these cost functions the similarity to the input images and the visibility of the seam are defined in the gradient domain, minimizing the disturbing edges along the seam. A good image stitching will overcome both photometric inconsistencies and geometric misalignments between the stitched images. This approach is demonstrated in various applications including generation of panoramic images, object insertion and stitching of object parts.

Key words: Gradient, mosaicing, feathering, seam, pyramid

INTRODUCTION

Image Stitching is a common practice in the generation of panoramic images and applications such as object insertion and object removal and super resolution.

Two images I_1 and I_2 capture different the portions of the same scene, with an overlap region viewed in both the images. The images should be stitched to generate the mosaic image I. A simple pasting of left region from I_1 and right from I_2 produces visual artificial edges in the seam between the images, due to differences in camera gain, geometrical misalignments etc.

The aim of the stitching algorithm is to produce a visually plausible mosaic with two desirable properties. First, the mosaic should be as similar to the input images, both geometrically and photometrically (Assaf *et al*., 2006). Second, the seam between the images should be invisible.

This study presents several cost functions for the above requirements and define the mosaic image as their optimum. The stitching quality is measured in the gradient domain. The mosaic should contain a minimum amount of seam artifacts, i.e., a seam should not introduce a new edge that does not appear in either I_1 or I_2. As image dissimilarity gradients of the mosaic image I are compared with the gradients of I_1, I_2. This framework is called GIST: Gradient Domain Image Stitching. Gradient is a vector. It states how much the image is changing. The magnitude of the gradient says how much the intensity is changing and the direction says in which direction it is changing. All the existing approaches namely, the optimal seam, feathering and pyramid blending work in the image domain. Optimal seam algorithms (Efros and Freeman, 2001; Davis, 1998; Agarwala *et al*., 2004) search for a curve in the overlap region on which the differences between I_1, I_2 are minimal. Then, each image is copied to the corresponding side of the seam. The second approach feathering (Uyttendaele *et al*., 2001) minimizes seam artifacts by smoothing the transition across the images. In Pyramid method (Adelson *et al*., 1984) different frequency bands are combined with different alpha masks. The objective is to join number of images to form a larger mosaic so that segment boundaries are not visible.

All these approaches either concentrate on the geometrical misalignments or photometrical inconsistencies but not both, the gradient approaches keep the mosaic similar to the input images both geometrically and photometrically.

The GIST approach is demonstrated in various applications including panoramic mosaicing, object insertion, object removal and removal of compression artifacts. The various advantages of using GIST is that it handles both geometric and photometric inconsistencies, small changes in position are also taken into account and it is invariant to the mean intensity of the image.

RELATED WORK

There are three main approaches to image stitching in literature, assuming that the images have already been aligned. Optimal seam algorithms (Efros and Freeman, 2001; Davis, 1998; Agarwala *et al*., 2004) search for a curve in the overlap region on which the differences between I_1, I_2 are minimal. Then, each image is copied to the corresponding side of the seam. In case the difference between I_1, I_2 on the curve is zero, no seam gradients are produced in the mosaic image I. However, the seam is visible when there is no such curve, for example, when there are globally smooth intensity differences between the images.

The second approach minimizes seam artifacts by smoothing the transition across the images. In Feathering or alpha blending, the mosaic image I is the weighted combination of the input images I_1, I_2. The weighting coefficients vary as a function of distance from the seam. In Pyramid method (Adelson *et al.*, 1984) different frequency bands are combined with different alpha masks. The objective is to join number of images to form a larger mosaic so that segment boundaries are not visible. A related approach is discussed in Peleg (1981).

Five most relevant papers are Image Quilting for Texture Synthesis and Transfer (Efros and Freeman, 2001), Mosaics of Scenes with Moving Objects (Davis, 1998), Digital Photomontage (Agarwala *et al.*, 2004), Eliminating Exposure Artifacts in Image Mosaics (Uyttendaele *et al.*, 2001), Pyramid Methods(Adelson, 1984). The approach used in Efros and Freeman (2001), Davis (1998), Agarwala *et al.* (2004) is Optimal Seam algorithms which concentrate only on geometric misalignments and not on photometric inconsistencies. The approach used in Uyttendaele *et al.* (2001), Adelson (1984) are Feathering and Pyramid method respectively. Both have the drawback that they concentrate only on intensity variations and not on geometrical misalignments. The approach in this study computes the mosaic image I by an optimization process that uses image gradients. Computation in the gradient domain was recently used in the compression of dynamic range (Fattal *et al.*, 2002), image in painting (Ballester *et al.*, 2001) and separation of images into layers (Finlayson *et al.*, 2002; Frankot and Chellappa 1988; Weiss, 2001).

GIST: GRADIENT DOMAIN IMAGE STITCHING

Preprocessing: The preprocessing step is to remove the noise from the input images by using a median filter. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. Like the mean filter, the median filter considers each pixel in the image in turn and looks at its nearby neighbours to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighbouring pixel values, it replaces it with the median of those values. The median is calculated by first sorting all the pixel values from the surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value. (If the neighbourhood under consideration contains an even number of pixels, the average of the two middle pixel values is used). Figure 2 illustrates an example calculation.

Image gradients: The gradient of an image measures how it is changing. It provides two pieces of information.

- The magnitude of the gradient tells us how much the image is changing.
- The direction of the gradient tells direction in which image is changing.

To illustrate an image is taken as a terrain, in which each point the height is given rather than the intensity. For any point in the terrain, the direction of the gradient Levin *et al.* (2004) would be the direction uphill. The magnitude of the gradient would tell how the height increases when a small step is taken uphill. Because the gradient has a direction and a magnitude, it is natural to encode this information in a vector. The length of this vector provides the magnitude of the gradient, while its direction gives the gradient direction. Because the gradient may be different at every location, it is represented with a different vector at every image location. The gradient can be computed by taking the first derivative in the x and the y direction respectively. Gradient in the x direction tells us how much the intensity changes when movement is there in the x direction and similarly gradient in the y direction computes the intensity change in y direction. Gradient can also be computed arbitrarily for any direction.

Computing the gradient: The gradient vector is formed by combining the partial derivatives of the image in the x direction and the y direction

$$\nabla I = \frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \qquad (1)$$

When the partial derivative of I is taken with respect to x we are determining how the image intensity changes as x changes. For a continuous function, I(x,y) it can be written as

$$\frac{\partial I}{\partial x}(x,y) = \lim_{\Delta x \to 0} \frac{I(x+ x,y)-I(x,y)}{\Delta x} \qquad (2)$$

In the discrete case, we can take differences at one pixel intervals. So we can take the difference between I(x,y) and the pixel before it, or the pixel after it.

$$\frac{\partial I}{\partial x}(x,y) = \frac{I(x+1,y)-I(x-1,y)}{2} \qquad (3)$$

Fig. 1: Stitching result

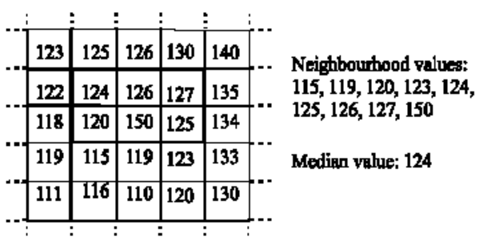

Fig. 2: Calculating the median value of a pixel neighbourhood

By similar reasoning,

$$\frac{\partial I(x,y)}{\partial y} = \frac{I(x,y+1)-I(x,y-1)}{2} \tag{4}$$

Gradient in any arbitrary direction: Image changes as we move from position by a small amount Δ in an arbitrary direction Θ which will take us to position ($x+\Delta\cos\theta$, $y+\Delta\sin\theta$) can be calculated as

$$I(x+\Delta\cos\theta, y+\Delta\sin\theta) = I(x,y) + \Delta\cos\theta \frac{\partial I(x,y)}{\partial x} + \Delta\sin\theta \frac{\partial I(x,y)}{\partial y} \tag{5}$$

Uses of the gradient:

- Use of gradients means that we are considering how the image changes with very small movement in position.
- Gradient is important in boundary detection.
- Change in intensity can be found as we move in any direction.

Gist1: Optimizing a cost function over image derivatives: The first approach GIST1, computes the stitched image by minimizing a cost function Ep. Ep is the dissimilarity measure between the derivatives of the stitched image and derivatives of the input images. Consider Fig. 1. Let I_1 and I_2 be two aligned input images. Let τ_1 (τ_2 resp.) be the region viewed exclusively in image I1(I2 resp.) and let w be the overlap region., with $\tau_1 \cap \tau_2 = \tau_1 \cap w = \tau_2 \cap w = \Phi$. Let W be the weighting mask image. The stitching result of GIST1 is defined as minimum of Ep with respect to I.

$$E_p(\hat{I}; I_1, I_2, W) = d_p(\nabla\hat{I}, \nabla I_1, \tau_1 \cup \omega, W) + d_p(\nabla\hat{I}, \nabla I_2, \tau_2 \cup \omega, U - W) \tag{6}$$

Where U is the uniform image, U(q) is the uniform image for all q and $d_p(j_1, j_2, \Phi, W)$ is the distance between J_1 and j_2 on Φ.

Fig. 3: Panorama Stitching

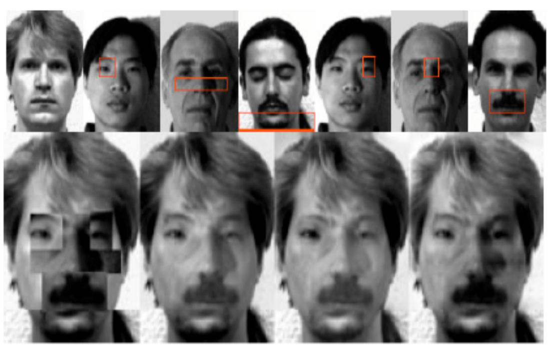

Fig. 4: Police application for generating composite portraits

$$d_p(J_1, J_2, \phi, W) = \sum_{\mathbf{q}\in\phi} W(\mathbf{q}) \, \| J_1(\mathbf{q}) - J_2(\mathbf{q}) \|_p^p \qquad (7)$$

In GIST1 the overlapping area is not removed and so image duplication arises. The selection of weighting mask is as follows

$$\begin{aligned} W_C(x,y) &= 1,\ x < c_x - d \\ &\tfrac{1}{2},\ cx - d = x = c_x + d \\ &0,\ c_x > d \end{aligned} \qquad (8)$$

$$\begin{aligned} W_1(x,y) &= 1,\ x < c_x - d \\ &c_x+d\text{-}x/2d,\ c_x - d = x = c_x + d \ldots(4.1.1.2) \\ &0,\ x > c_x + d \end{aligned} \qquad (9)$$

Gist2 stitching derivative images: A simpler approach to stitch the derivative of the input images.

- Read the input images.
- Compute the derivative of the input images.
- Find the overlapping region by using histogram method and remove it from one of the images.
- Align and stitch the images.

Gist applications:

Stitching panoramic views: The input images were captured from different positions and were aligned by a two-dimensional parametric transformation as shown in Fig. 3.

The aligned images contained local misalignments due to parallax and photometric inconsistencies due to difference in camera settings and camera settings. The above figure shows the output of the GIST approach.

Stitching object parts: Object parts from different images are combined to generate the final image. This can be used, for example, by the police in the construction of a suspect's portrait from parts of faces in the database (Fig. 4).

Object insertion: In this application, objects are to be inserted seamlessly into an image. This paper's approach overcomes photometric inconsistencies and all misalignments (Fig. 5).

(a)

(b)

(c)

Fig. 5: Object insertion

The above figure shows the image of a woman with closed eyes is fixed by replacing the facial area. The inserted facial part was captured at a different head orientation, which causes misalignments between the inserted and original face image. Still, the algorithm managed to create a seamless result.

CONCLUSION

Image Stitching is presented as a search for an optimal solution to a image quality criteria. The paper discussed different methods for stitching and focused on the novel approach that optimizes over the derivatives. Even though each stitching algorithm works better for some images and worse for others the GIST approach always works well and handles both geometric misalignments and photometric inconsistencies. It will be useful to explore alternative criteria for image quality using additional image features and results on statistics of natural images (Simoncelli, 1999; Wainwright and Simoncelli, 2000).

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