Using Geometric Blur for Point Correspondence

Nisarg Vyas

Electrical and Computer Engineering Department, Carnegie Mellon University, Pittsburgh, PA

Abstract— In computer vision applications, point correspondence plays an important role. Here, we present a technique called geometric blur to find point correspondences between two different images, even in the presence of affine distortions. We compare the results of this technique with other prevalent techniques for finding point correspondences, such as SSD (Sum of Squared Differences) with uniform Gaussian blur. Experimental results are shown on various face images and other object images.

***Index Terms* — point correspondences, geometric blur, interest points, object detection and recognition, SIFT**

I. INTRODUCTION

Point correspondence between two or more images is crucial component for many computer vision and image analysis tasks. Most methods for 3D reconstruction, object detection and recognition, image alignment and matching and camera calibration techniques assume that feature points were extracted and put to reliable correspondence. Hence, this problem is a key step in most computer vision applications, and so far there does not exist any completely automated method to solve this problem reliably.

There have been considerable efforts to define correspondence between images based on local interest points, firstly used for stereo image matching by Moravec [1] before two decades. The corner detector of [1] was substantially improved by Harris et. al [2], which has been widely used for many computer vision and image matching tasks. Zhang et. al [3] matched Harris corners between two images by using correlation window of the neighborhood surrounding the Harris corners. Schmid and Mohr [4] used rotationally invariant descriptor of the local image region based on Harris interest points to match set of images. Traditionally, Harris corner detector is very sensitive to changes in image scale. Lowe [5][6] extended local descriptor-based approach to achieve scale invariance, which is known as Scale Invariant Feature Transform (SIFT).

The SIFT operator finds characteristic scale of the interest point by finding an extrema of the interest point in a Difference of Gaussian (DoG) pyramid. The filter used for constructing DoG pyramid is a Gaussian blur filter of size 3x3. Berg et. al [7] argue that uniform blur filter might not be correct way to apply blurring, when one is interested in finding point correspondences. Moreover, they provide a new blurring operator called ‘*Geometric Blur*’.

This paper compares results of experiments based on simple Sum of Squared Differences (SSD) based image patch matching technique, used on uniform Gaussian blurred neighborhood and geometric blurred neighborhood over Harris interest points.

The paper is organized as follows. Section 2 discusses Geometric Blur and the underlying intuition behind using it for finding point correspondences and Section 3 discusses results of using different blurring techniques for solving the problem. In last section, we conclude with some future directions of this work.

II. GEOMETRIC BLUR

Geometric Blur is a notion of blurring, developed especially to compute measure of similarity between image patches (templates). It targets making the correspondence procedure more by making the templates discriminative and the matching robust.

The standard strategy employed in the vision community to find similarity measure between two image patches is the coarse-to-fine way approach by

Manuscript received Dec 19th, 2005.

* - The author is affiliated with the Electrical and Computer Engineering Department, Carnegie Mellon University, Pittsburgh, PA 15213,

contact e-mail address for the author is : nisarg@ cmu.edu

building Gaussian pyramids. At each level of the pyramid, the image is subsampled and convolved with the Gaussian filter in the spatial domain. Gaussian blur introduces a positional blur uniformly at each level. Using a uniform blur at each level of the pyramid creates a positional uncertainty about the central region of the image patch, which may be incorrect thing to do when one is interested in finding correspondence. The situation even worsens when there are affine distortions present in the images.

We assume that under the presence of an affine distortion, that fixes a single point, the distance the piece of signal changes is linearly proportional to the distance that the piece of signal is away from the feature point. This assumption can be encoded in the filter by making use of a spatially varying blurring kernel. Hence, instead of blurring by Gaussian filter of constant standard deviation (σ), we propose using a variable standard deviation, in linear proportion with the distance. (e.g. $\alpha|x|$).

The following figure shows the difference between using uniform Gaussian blur filter and the geometric blur with spatially varying Gaussian Kernel.

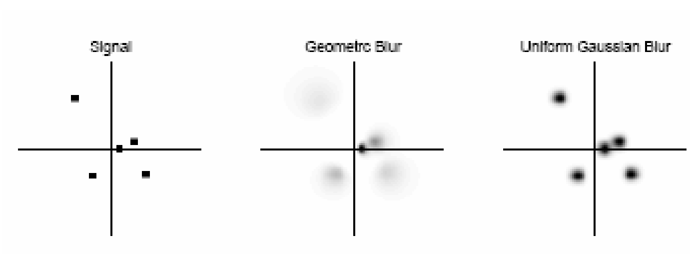


Figure 1: Comparison between geometric blur and uniform Gaussian blur. Geometric blur blurs the signal more farther from the origin (Figure Courtesy [7])

Geometric blur is more effective when applied to sparse signals[7], hence we have compute geometric blur on 4 distinct gradient channels: i) positive gradient in x direction, ii) negative gradient in x direction, iii) positive gradient in y direction and iv) negative gradient in y direction.

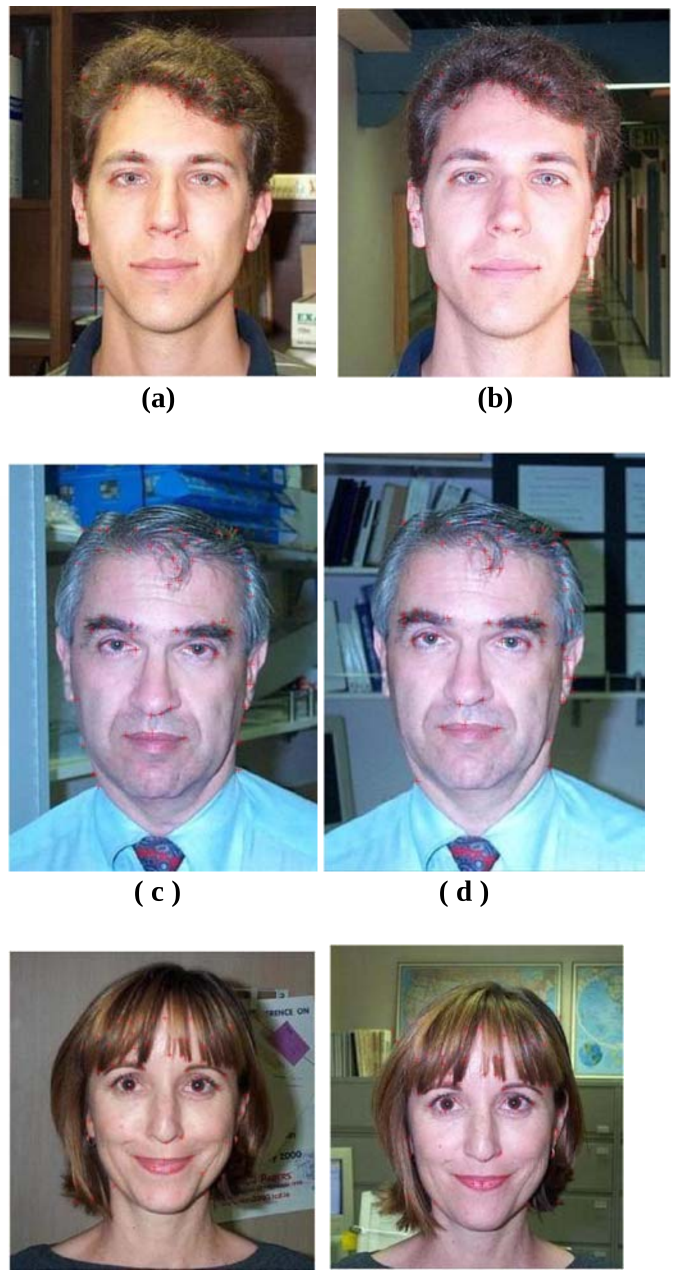
III. EXPERIMENTS

Database

We have used face subset of the Caltech 101 dataset [8] of object catergories for our point correspondence experiments.

Results

We conducted Harris corner detection from set of pairs from the dataset we used. Figure 3 displays the outputs of applying Harris corner detector for example pairs of images.



(a) (b)

(c) (d)

(e) (f)

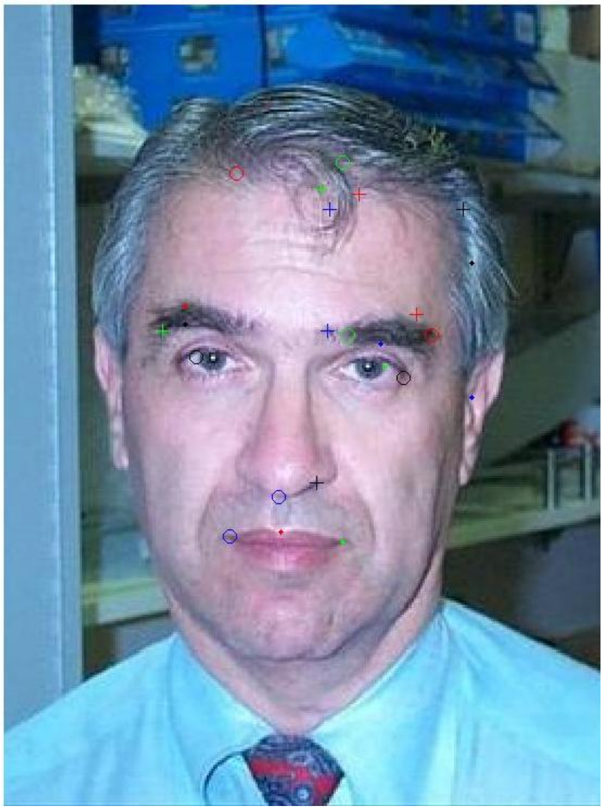
Figure 3 (a-f) – Best 50 Harris interest points for image pairs, the interest points are marked with '+'

We found out 50 most prominent interest points from each pair of images by using Harris corner detector. Given one interest point in the first image, we attempt to find a matching interest point in the second image The images are split into four sparse gradient channels as described in the previous section, and the geometric blur descriptors are extracted from the selected interest points. The matching of the descriptors is carried by Sum of the Squared Differences (SSD) operator over the descriptors. The geometric blur descriptor is taken by subsampled points of concentric circles around feature points. Geometric blur descriptor of each feature point consists of total 10 concentric circles, with each circle having 8 points subsampled. Calculation of geometric blur is carried out over four gradient channels. Thus, we get the final geometric descriptor having total of 320 dimensions per each feature point selected by Harris corner detector.

Figure 4 displays the results of the point correspondences for the image pairs. The images are displayed on larger scales so that the same color coded correspondence points can be visualized in both the image pairs.

(b)

(a)



(c)

(d)

(e)

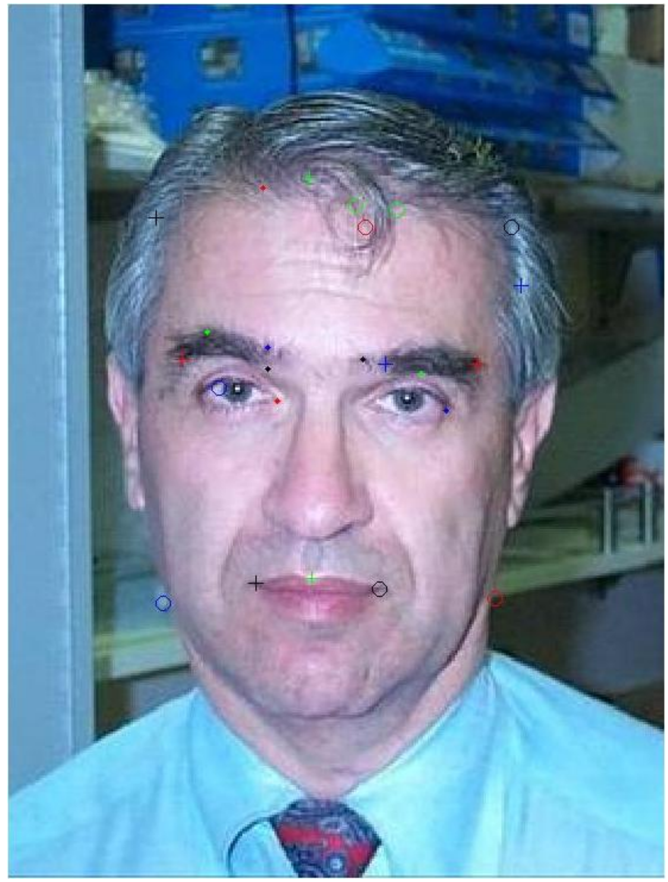
(f)

Figure 4 – point correspondences derived from geometric blur extractor technique, the correspondence is established between images (a)-(b) , (c)-(d) and (e)-(f), the correct correspondence is marked with same color and same shape at the similar locations in the pair of images. First pair has 17 correct matches, second pair has 18 correct correspondences and the third pair has 16 correct correspondences.

For comparison, we established point correspondences using SSD for uniform Gaussian blur for the same images, and sample results are shown in figure 5.

(a)

(b)



(c)

(d)

(e)

(f)

Figure 5 – point correspondences derived from SSD

on uniform Gaussian blur, the correspondence is established between images (a)-(b) , (c)-(d) and (e)-(f), the correct correspondence is marked with same color and same shape at the similar locations in the pair of images. First pair has 11 correct matches, second pair has 15 correct correspondences and the third pair has 12 correct correspondences.

We tested on 30 pairs of facial images, once with same person featuring in image pairs, and once with different persons featuring in image pairs. The performance for both geometric blur and uniform blur techniques can be summarized from the following table. As it can be seen from the table, geometric blur descriptor performs much better than the uniform Gaussian blur.

Description	Average number of successful correspondences out of first 25 correspondences	Accuracy Percentage
Geometric blur, Same person featuring in image pairs	17	68 %
Uniform Gaussian blur, Same person featuring in image pairs	12.2	48. 8 %
Geometric blur, different persons featuring in image pairs	10.4	41.6%
Uniform Gaussian blur, different persons featuring in image pairs	7.8	31.2 %

IV. Conclusion

In this paper, we propose to use geometric blur for finding point correspondences, and we claim that it is more effective than the normal uniform descriptors used for the task on hands. We apply both types of descriptors for finding correspondences on the facial images. Upon comparison of both descriptors, our results convey that geometric blur descriptors perform much better than the uniform Gaussian blur descriptors for the task of point correspondence. These early experiments provide motivation of using geometric blur application which require template matching, such as stereo vision and object detection. It would be interesting to combine geometric blur technique with successful point correspondence strategies such as SIFT, which use uniform Gaussian blurring method till this date.

Acknowledgement

The author would like to thank Prof. Alexei A. Efros for providing valuable insights and for ftuiful discussions regarding project experiments.

References

[1] H. Moravec, Rover visual.object avoidance, In International Joint Conference on Artificial Intelligence, Vancouver, Canada, pages 785-790, 1981

[2] C. Harris and M. Stephens, A combined corner and edge detector, In fourth Alvey Vision Conference, Manchester, UK, pages 147-151, 1988

[3] Z. Zhang, R. Deriche, O. Faugeras, and Q. T. Luong, A robust technique for matching two uncalibrated images through the recovery of the unknown epipolar geometry, Artificial Intelligence, issue 78, pages 87-119, 1995

[4] C. Schmid and R. Mohr, Local grayvalue invariants for image retrieval, in IEEE transactions on Pattern Analysis and Machine Intelligence, issue 9, volume 5, pages 530-534, 1997

[5] D. G. Lowe, Object recognition from local scale-invariant features, In International Conference on Computer Vision, Corfu, Greece, pages 1150-1157

[6] D. G. Lowe, Distinctive Image Features from Scale-Invariant Keypoints, International Journal of Computer Vision, 2004

[7] A. C. Berg and J. Malik, Geometric Blur for Template Matching, In International Conference on Computer Vision and Pattern Recognition, 2001

[8] L. Fei-Fei, R. Fergus and P. Perona, Learning generative visual models from few training examples: an incremental Bayesian approach tested on 101 object categories. In International conference on Computer Vision and Pattern Recognition, 2004