SUPER RESOLUTION OF COLOR IMAGE FROM MULTIPLE LOW RESOLUTION IMAGES

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Abstract- Super-Resolution (SR) image reconstruction is the procedure of joining several spatially misaligned low resolution (LR) images into a single high resolution (HR) image. In this route accurate image registration is the key step and homography serves as basis for image registration. Homography estimation between LR images was done using Harris corner detector and Random Sampling Consensus (RANSAC). Harris corner detector finds the corner points of LR images and RANSAC finds the transformation matrix by filtering out mismatched points. A new SR approach is proposed in which LR images are then projected to HR grid using transformation matrix. New SR approach avoids iterative process for convergence making computation faster for better results. Remaining unfilled spaces is HR image are filled with interpolation.

Keywords- Super Resolution, Correlation, Homography, Image Registration, Harris Corner Detector, RANSAC, Bi-cubic Interpolation.

I. INTRODUCTION

The Image registration is the procedure of obtaining transformation matrix that brings spatial alignment between two images. Many theoretical and physical limitation of imaging systems often provides us low resolution images of the same scene. Every LR image got some information. Super resolution approach gathers this information from multiple LR images and combines it to get a HR image. Basic assumption is the availability of multiple images of the same scene to obtain different information in each LR image, such that some relative motion must exist between LR images or video sequence. The main objective of Super-Resolution (SR) is to recover a high resolution (HR) image from multiple Low resolution (LR) images.

First step for thorough analysis of the SR image reconstruction is to devise an observation model that connects the HR image and LR images. We consider desired HR image X of dimension M x N and k number of LR images as Y having dimension m x n. In common imaging system an original scene during capture suffers from warping due to scene motion or change of camera position M, motion and sensor blur B and down sampling factor D with noise n gives us LR image. This is the basic Observation model and is shown as a block diagram in Fig 1. In equation form it can be written as

$$Y_k = DB_kM_kX + n_k \quad (1)$$

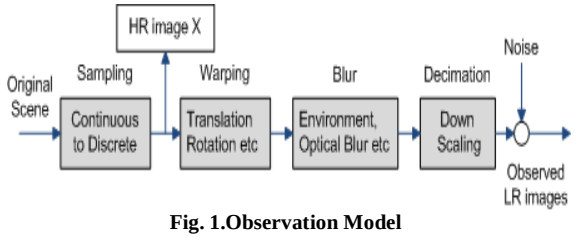


Fig. 1.Observation Model

SR methods are broadly classified into two main categories i) example based Super-Resolution (SR) and ii) classical multi images Super-Resolution (SR) reconstruction. In example based SR, high and low resolution patches are learned after resemblance from a database of high and low resolution image pairs.

Significant work has been done in the past on classical SR reconstruction. Hsieh and Huang continued the iterative back projection approach (IBP) initially proposed by Irani and Peleg but used Normalized cross correlation (NCC) as registration technique instead of affine model proposed by Keren which was valid for small displacements. They also extended the work for video super resolution but again it has no distinctive solution due to inverse problem. Secondly this is an iterative and slow method.

Xie and Zhang extended the work of Ozkan and Tekalp by imposing new constraints on Projection onto convex sets (POCS) which is widely used. In POCS method the main difficulty is to set proper projection function for convergence therefore it has slow convergence, high computational cost and non-uniqueness of the solution. Furthermore for image registration affine model is used that is limited to small displacements between images. Results are compared with this method in the final section.

Some other sophisticated SR approaches were also introduced. Jian and Zongben used gradient profile prior for Super-Resolution but under noisy condition this method is inaccurate. Finally Nasir and Stankovic proposed new registration method based on RANSAC and SIFT (Scale Invariant Feature Transform) and BP (Belief Propagation) and used super resolution algorithm of Elad and Milanfer. This is stochastic approach based on ML estimators which must have prior knowledge and involves complexity. Various other SR techniques have been discussed.

II. SYSTEM OVERVIEW

This section explains the procedure for obtaining projective matrix (homography) that is used for projecting LR images to HR grid. We use grayscale image for projective matrix calculations and project all three (RGB) channels using this matrix.

A. Harris Corner Detector

Harris corner detector finds the corner points of an image proposed by Harris and Stephens. Corner is a point in an image where intensity changes in all directions. R in equation (2) is threshold which is higher for corners where H is the covariance matrix and K is the empirical constant varying from 0.04 to 0.06. I_x and I_y are gradients at each point of an image. Now Corners are the points where R is greater than our defined value.

$$R = \det(H) - K(\text{trace}H)^2 \quad (2)$$

Where

$$\mathbf{H} = \begin{bmatrix} \sum \mathbf{I_x^2} & \sum \mathbf{I_x I_y} \\ \sum \mathbf{I_y I_x} & \sum \mathbf{I_y^2} \end{bmatrix} \quad \mathbf{(3)}$$

B. RANSAC

After finding corner points for Reference LR image and first Test LR image, we need to find correspondence between points that are maximally correlated with each other. Points not having any correspondence are rejected. Putatively matched points are then used for the calculation of projective matrix. But inaccurate results are obtained due to outliers present in these points. The Random Sampling Consensus (RANSAC) is a robust parameter estimation approach proposed by Fischler and Bolles. It was designed originally for dealing with large amount of outliers in the input data and makes a useable model by selecting minimum points.

Correct matching corners are classified as inliers and remaining as outliers. For each four corners between two reference and test image projective transform with maximum inliers is found.

C. Homography

Homography is a direct mapping between two projection planes with the same center of projection. Image of planar objects taken by offset cameras are also related by it.

Let Reference images corners are denoted by coordinates $P(x_n, y_n)$ and test image corners are $Q(x_n', y_n')$, where n is the number of corners. We want to find projective matrix A such that

$$Q = A\,P \quad (4)$$

By Least Square method (LSM) and Singular Value Decomposition (SVD) of B^TB and reshaping it we get projective matrix A of size [3x3] given by Hartley and Zisserman. Where matrix B is of size 2n x 9shown in the equation form as

$$B = \begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1x_1' & -y_1x_1' & -x_1' \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1y_1 & -y_1y_1' & -y_1' \\ & & & & & & \vdots & & \\ & & & & & & . & & \\ & & & & & & . & & \\ x_n & y_n & 1 & 0 & 0 & 0 & -x_nx_n' & -y_nx_n' & -x_n' \\ 0 & 0 & 0 & x_n & y_n & 1 & -x_ny_n & -y_ny_n' & -y_n' \end{bmatrix} \quad (5)$$

This procedure is performed for all the test images and their projective transform is found. As homography is variant to scale we find projective matrix twice, first at normal image scale and secondly zooming image two times using Bi-cubic interpolation. Then from these two matrixes we find nearly scale invariant homography.

III. PROPOSED METHOD

As discussed in the previous section, after getting projective transform next step is to project each LR image to HR grid. Proposed Scheme is shown in the Fig 2.

For this purpose we use a simple novel approach that is computationally inexpensive. We use pixel locations (indexes) and zooming factor as a reference for projection. For this cause accurate projective matrix calculation is crucial.

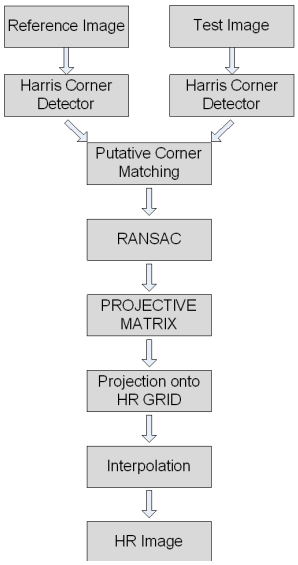


Fig. 2.Proposed Scheme

In first step reference image pixel locations matrix is multiplied with each corresponding LR image projective matrix to obtain new pixel locations of each LR image. This shifting is global so that all the image pixel locations of an image are shifted with the same magnitude. All these pixel locations are then multiplied by zooming factor and HR image pixel locations are obtained for all the test images.

In second step each LR color image is projected to HR color image grid using HR pixel locations obtained in first step. All three color channel values (RGB) are projected separately to HR image corresponding color channels. We take medians of two or more pixels mapping to same location in HR grid, if there are more images, it will reduce the effect of noise and blurring. Locations in the image are integer values but the new pixel locations after above process can be float values. For the purpose of keeping original pixel values, instead of interpolating pixel values to integer locations, we find pixel location nearest to integer locations with the threshold e = 0.2. If a new pixel location is (1.1, 5.2) we consider it (1, 5) and if a new pixel location is (1.4, 5.3) it is rejected.

After the projection of pixels onto HR grid, Bi-cubic interpolation is done at locations where no pixel is mapped by finding unfilled locations. This is the main advantage of the proposed method that we project original values that leads to better results instead of projecting interpolated values. Secondly, there is no iterative process for convergence which makes computation low and makes our method robust. As bi-cubic interpolation softens the image slightly we finally do some sharpening with Laplacian filter as a post processing of HR image.

IV. EXPERIMENTS AND RESULTS

In this section we verify our proposed method by comparing results with some other commonly used techniques. Simulation was run in the MATLAB using zoom factor = 4.

Two cases were considered for the experiments. First was Lena image as ideal case with no noise and blur. Four images of 256 x 256 were generated from a 512 x 512 image by selecting alternate pixels. For POCS method these LR images were registered by affine method and we used homography as registration in our method to see the effect of image registration. Then HR image of 1024 x 1024 was constructed by these methods.

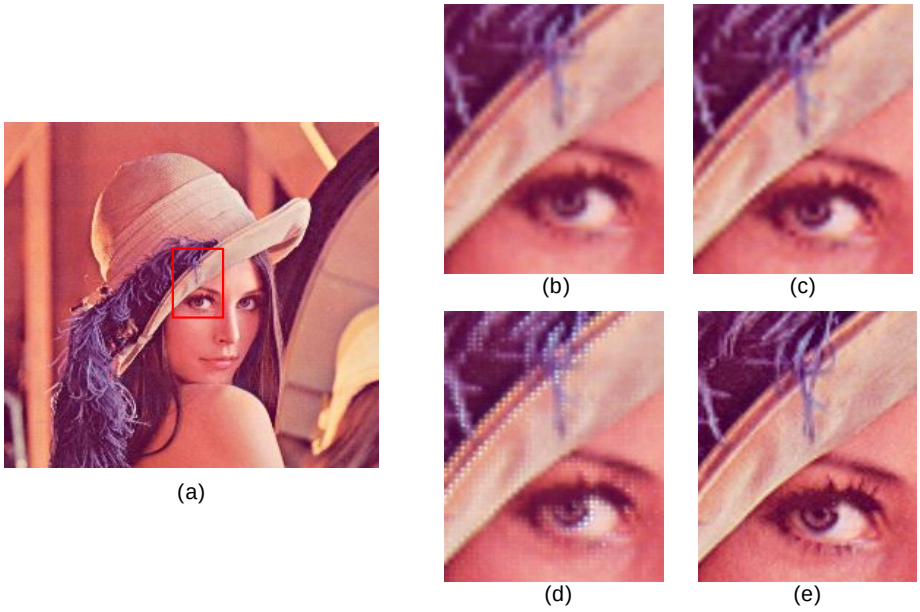


Fig. 3. Test image and cropped 4x zoom samples comparison (a) 256 x 256 Test image (b) Bi-linear (c) Bi-cubic (d) POCS method (e) Proposed Method

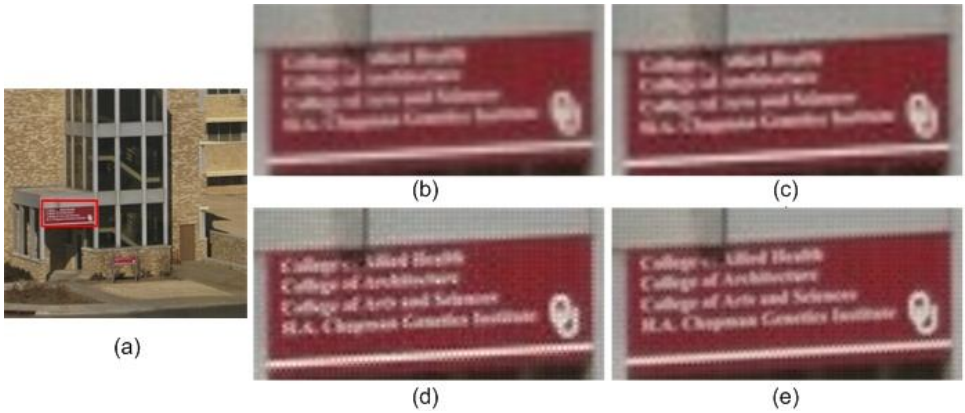


Fig. 4. Test image and cropped 4x zoom samples comparison (a) 300 x 300 Test image (b) Bi-linear (c) Bi-cubic (d) POCS method (e) Proposed Method

We compared the results of our method Fig 3(e) with Bi-linear interpolation Fig 3(b) Bi-cubic interpolation Fig 3(c) and Projection onto convex sets Fig 3(d). Results are shown in Fig 3.We can see that in (e) image registration is correct and far better than (d). Secondly SR image constructed by (e) has more detail and stronger edges which are clearly visible e.g. eye lashes and hat in (e). Similarly image in (e) is sharper and brighter than all other images.

In second case ten offset images of 300x300 were taken. These images have translational offsets between each other. These images include atmospheric and camera sensor blurring and slight noise as well. In this case we used homography as registration for both POCS and our method to see the efficacy of the proposed method. SR image was created using all above mentioned methods and then compared with our method. Results are shown in Fig 4. In Fig 4, our method Fig 4(e) outperforms Fig 4(b), (c) in detail and sharpness. Due to minimum noise and artifacts in Fig 4(e) it has clearer edges and color than Fig 4(d). Results given in Fig 3 and Fig 4 demonstrate that our proposed method recovers the image sharpness and detail with minimum artifacts.

CONCLUSION

In the current paper a new SR method is proposed that uses Homography as registration between multiple images and can be used for both grayscale and color images. This method is based on corners of an image. Most of the traditional SR techniques involve interpolation for initial guess of HR image but in this paper we used only original pixels from LR images. This simple method is fast due to no convergence criteria. Analysis of test images using proposed method gave us satisfactory and encouraging results and shown above. In the feature our plan is to extend this proposed method for video super resolution.

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