ITERATIVE SUPERRESOLUTION RECONSTRUCTION FROM MULTIPLE IMAGES WITH AREA SAMPLING SENSOR MODEL

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ABSTRACT

Oversimplification of the model for image acquisition by CCD cameras has detrimental effects in superresolution applications. We propose a model which assumes that image pixels are generated from a hypothetical image created by an imaginary high resolution image sensor. This way, superresolution is no longer an upsampling process but an imitation of an imaginary high resolution sensor. We obtained superior results compared to related models.

I. INTRODUCTION

Since image acquisition and processing become practical by the developments in the computing technology, the generation of a single high quality image from a set of images of the same scene has drawn considerable attention due to the enormous possibilities it offers in many imaging applications. Generating high quality printouts from video sequences and satellite imagery are just the most common applications of superresolution restoration. The advancements in imaging technology paved the way to higher resolution and higher quality images. However, this did not eliminate the desire for better images even we have much better images than we used to just couple of years ago.

Superresolution restoration requires multiple images of the same scene. The references [1-7] are some examples of different directions taken in the methodology for the resolution enhancement. As emphasized in the references, the difference between imaging parameters of these images are essential. Had they been the exact copies of the same picture, it would not be possible to extract additional information out of them. But such image sets can be used to reduce the uncorrelated noise in them by just taking the average of them. In order to obtain a superresolution image, the differences created by spatial motion, different blur and/or such, are necessary, Assuming that one has the images satisfying this requirement, the generalized methodology for superresolution generation can be simplified as;

1. On a reference coordinate system, register the images in subpixel level to have irregularly spaced sample points (pixels) of a hypothetical image.
2. From these irregularly spaced samples, estimate an image with regularly and densely spaced samples. [10]

The success of the superresolution ultimately depends on the accuracy of the subpixel registration [11-12] and the accuracy of the imaging model. The registration process and superresolution image generation can be handled as either separate or combined processes. Many researchers assumed that they have the registration parameters and attacked on the superresolution generation. POCS (projection onto convex sets), on the other hand, runs them in parallel since they are deeply interconnected. The dependency on the subpixel registration and the imaging model remains intact.

II. THE MODEL

A generally accepted imaging model for superresolution purposes has separate spatial translation and rotation blocks for every image obtained from image sensor. Reader is referred to [13] for a through modelling of CCD sensors. The sensor surface is populated by the square photoactive cells each of which generate an electrical charge proportional to the number of the incident photons. The charge is converted to a voltage value by the sensor electronics which later quantized and digitized. The i^{th} pixel value is usually modelled by a spatial integration of the light intensity field as

$$P_{Li} = \int_S I(z)dz \qquad (1)$$

where $I(z)$ is the continuous light intensity function at the sensor plane and S is the photoactive area of the sensor cell surface. Common optical blur, PSF_{lens}, and the blur caused by the integration, PSF_{sensor}, are separated in the camera model. PSF_{lens} is usually assumed to be spatially invariant Gaussian blur function and the same for all images. PSF_{sensor}, on the other hand, is a box function as described. In some superresolution related studies these PSFs are convolved to simplify the iterative processes [14]. In many others [2, 3, 5, 7] PSF_{sensor} is completely ignored and superresolution is handled as if it is an upsampling operation where it is assumed that the downsampling was done after a Gaussian blur filter (low pass filter). [4] leaves the selection of PSF_{sensor} to the implementation and aims to prove that their algorithm converges to a minima for reasonable cases of the selection. In [15] a summary on resampling and related kernels is given. In this paper, however, we propose that imaging process should not be oversimplified as such.

We favour a downsampling model depicted in Figure 1. Bigger square in Figure 1 is a sample sensor cell from which the actual image pixel values are obtained. The smaller squares are the hypothetical sensor cells which we assume high resolution (HR) image pixel values would be generated if there were such a sensor.

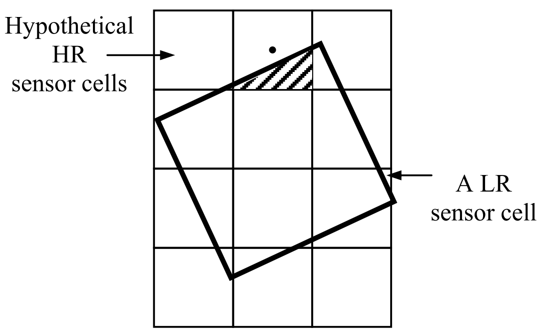

Figure 1. Overlapping areas of HR and LR image pixels are used as weights in calculation of LR pixel value

We inherently assume that low resolution (LR) pixels are generated by the weighted sum of the corresponding HR pixels. The weights, as depicted by the dashed area in Figure 1, are determined by the intersection areas of HR and LR sensor cells. Assuming that the photo-activity of the sensor cells are homogenous within the cell and among all cells a discrete summation can be written in terms of the intersection areas as

$$P_{Li} = \sum_j w_j P_{Hj} \tag{2}$$

where w_js are the normalized intersection areas and P_{Hj}s are the HR pixel values.

Figure 2 shows where the hypothetical HR image is in the model. PSF_{sensor_h} reflects the integration over the surface of the small hypothetical sensor cells, i.e. the small squares shown in Figure 1. Since no action has been taken to correct PSF_{lens} it is in the path of HR image too. We believe that unless a blur estimation step is added to the restoration process, any blur block assigned by guess-work should be approached by caution since it will probably be incorrect/inaccurate. The common blur block is, therefore, removed later in the modelling process and left for the future work. There exist many examples of blur removal, in the literature [8-9], which can be applied separately after the superresolution restoration.

Since one of the LR images is selected to have zero translation and zero rotation prior to registration, we shall easily remove one of the translation-rotation pair and assume that HR image is in line with this LR image. The imaging blocks shown in Figure 2 can then be arranged to reflect this as shown in Figure 3 where TR_ks represent translation and rotations in discrete domain and PSF_{sensor_k}s are just the calculations of LR pixels from the intersection areas as shown in Figure 1.

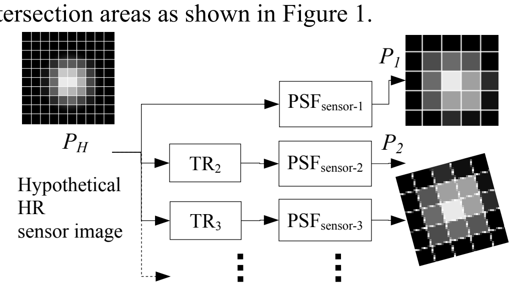

Figure 3. Discrete equivalent of the imaging model.

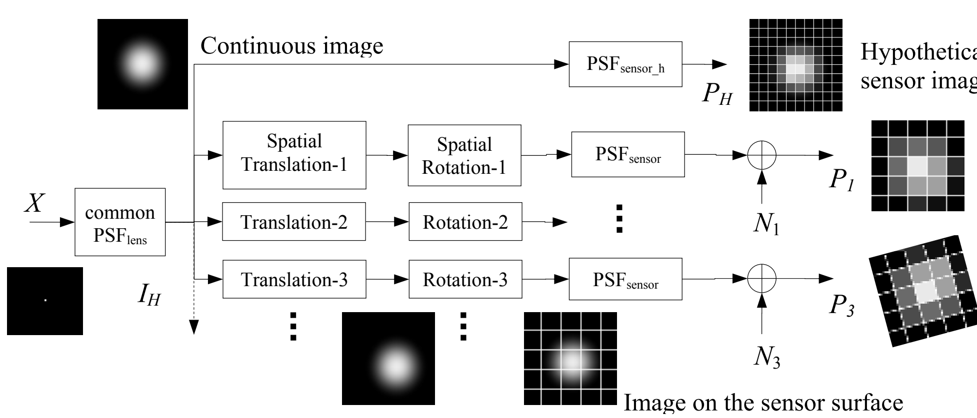

Figure 2 Imaging model showing the hypothetical sensor image.

Assuming that TR_ks are known a priori, the superresolution task is then to find hypothetical HR image that satisfies all LR images. Since the inverse problem is ill-posed, backprojection algorithms are preferred and that is the way we follow in this study.

III. ALGORITHM AND THE TEST RESULTS

The standard backprojection algorithm implemented with embedded steps to calculate the intersection areas is shown in Figure 4.

```
Estimate an initial HR image
For each TRk
  Apply TRk to HR estimate
  Determine overlapping areas for
      each HR/LR pixel
  Calculate HR pixels
  Calculate the difference between
      estimated and original LR
      images
  Update HR estimate according to
      the differences
Loop until desired/accepted error
levels for each image
```

Figure 4. Iterative superresolution restoration.

First estimate of HR image is obtained by just upsampling the base LR image (the one with zero translation and rotation) using simple nearest neighbour algorithm.

In order for a fair comparison of the different techniques simulated LR images with known registration parameters has to be obtained. As in many references, LR images are obtained by local averaging using (2). Another choice would be sub-sampling after a low-pass filtering. These two are generally accepted to be equivalent.

Figure 5 shows two LR images with two different translation and rotation parameters generated from 'city' HR image. The total of 4 differently translated and rotated LR images are used as inputs to the algorithm.

Figure 5. Rotated-shifted two LR versions of city image.

Three techniques are compared. The bicubic interpolation is not actually a superresolution technique based on the arguments we made at the introduction section. However, it is widely used to enlarge low resolution pictures. The second technique uses the same algorithm given in Figure 4, but instead of overlapping areas of the squares, a Gaussian weight function (PSF) is used. The results shown for the Gaussian weight function are the best of this technique after several trials. Since no algorithm is used to determine the optimal Gaussian function, we are forced to try and find the best. The third technique is the one that uses overlapping areas.

Table 1 shows the SNR results after 5 iterations in iterative techniques; Gaussian weight function and weights calculated from overlapping areas. Bicubic interpolation technique involves no iteration and uses only one LR image. Since no other image is involved in bicubic interpolation technique no additional detail could be brought in to the generated HR image.

Table 1
SNR after 5 iterations

	Bicubic	Gaussian	Areas
Lena	29.51	31.33	34.82
City	24.70	26.69	30.05
Cameraman	25.99	28.16	31.43
Montego	23.96	25.89	28.70

From the very first iteration, areas technique performed better than other two techniques. This is largely a result of the better simulation of the CCD cells. Gaussian weights technique also produced good results but the weights are not equal to the overlapping areas, so it is not a good representation of CCD cells.

IV. CONCLUDING REMARKS

We assumed that HR image is obtained by a hypothetical CCD cell array and used overlapping areas of the HR and LR CCD cells to model downsampling operation and iteratively generate the HR image using the model. A better approach would be the combination of optical blur and PSF_{sensor}. The weights would, of course, a lot more difficult to calculate in that case. We also believe that unless the optical blur represented by PSF_{lens} is accurately estimated or known a priori, estimations of PSF_{lens} would have a detrimental effect on the result. Another approach worth to study on is to embed PSF_{lens} estimation into the iterative restoration process. But the best contribution would be in the area of subpixel registration of images, since entire restoration process relies on the accuracy of it. It is always easier to work on simulated images based on the simple assumption of global rigid motion. In real life consecutive images however, several other issues have to be faced and handled. Our next study shall be on such motion models like local motion in real CCD output.

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