Super-Resolution of License Plate Images using Algebraic Reconstruction Technique

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***Abstract*—In this paper, an iterative super-resolution reconstruction method is introduced for license plate recognition. A high-resolution image of the license plate is reconstructed by fusing the information derived from a set of subpixel shifted low-resolution images. The reconstruction problem is formulated as a system of linear equations that is solved by using the simultaneous algebraic reconstruction technique (SIRT). Simulation experiments show that SIRT can reconstruct a HR image with superior quality compared to conventional super-resolution reconstruction methods.**

***Index Terms*—super-resolution, reconstruction, SIRT, algebraic reconstruction technique, license plate**

I. Introduction

Vehicle license plate detection from surveillance cameras is widely used in traffic monitoring and control systems. Deciphering license plates based on video sequences is challenging [1]. Surveillance cameras have limited spatial resolution, which may not always suffice to resolve the alpha-numeric characters from the license plates. Super-resolution methods are often required to reconstruct a high resolution (HR) image from a set of subpixel-shifted low resolution (LR) images. Fundamentally, such a task involves dealiasing and deblurring. To improve the readability of the plates, several methods have been suggested in the past. For example, Zhang et al. suggested a method to enhance only the character pixels while deemphasizing the background pixels [2]. In [3], Li et al. presented a bilinear interpolation scheme to enhance license plates. Cui and Huang [4] described a multiframe scheme for the extraction and enhancement of alpha-numeric characters in license plates. The authors in [5] proposed a robust Maximum a posteriori (MAP) based method with discontinuity adaptive Markov random field prior for enhancing edges in reconstruction process. A generalized discontinuity-adaptive Markov random field (DAMRF) model has been also used in [6] to make license plate numbers more legible. Kang et al. [7] presented an iterative image reconstruction scheme to remove motion blur.

Iterative reconstruction schemes are based on minimizing the difference between the simulated (i.e., computed) LR images and the observed (measured) LR images. The simulated LR images are computed from an imaging model including blur and subsampling. In each iteration, the error (difference) between simulated LR images and the observed LR images redistributed across the current estimate of the HR image. This process is repeated iteratively to minimize the energy of the error.

In this paper, SIRT is introduced in the field of license plate reconstruction to increase the spatial resolution of a license plate image from a set of LR images in an iterative reconstruction framework. SIRT has been successfully applied in CT and electron tomography [8], however, to the authors' knowledge, it has not yet been transferred to the domain of reconstructing a HR image from a set of LR camera images. While in tomography the projection values are modelled as line integrals of the unknown object, in camera imaging, the LR camera pixel values are modelled by a combination of an orthographic projection, spatial averaging (blurring) and subsampling of the unknown HR image.

After introducing basic notations and concepts in Section II.A, an overview of the SIRT algorithm is given in Section II.B, which will be focused on the reconstruction of a HR image from a set of LR images. In Section III, results are presented and discussed for simulated as well as experimental datasets. Finally, in Section IV, conclusions are drawn.

II. Method

A. Imaging Model

Let $\{y_i\}_{i=1,\ldots,d}$ represent a set of d low resolution (LR) images of size $M\times N$. It is assumed that these images are acquired under orthographic projections, and that individual scene motions can be modelled as affine transformations. The high resolution (HR) image that we want to reconstruct from $\{y_i\}$ is represented by x. We

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model each LR image as a noisy, uniformly downsampled version of the HR image, which has been shifted and blurred. If D denotes the downsampling operator, G the blurring operator and A the affine transform that maps the HR grid coordinate system to the LR grid system, we have:

$$DGAx+n=y. \tag{1}$$

This can be rewritten to:

$$Wx+n=y. \tag{2}$$

where $W=DGA$ is the complete system matrix. The reconstruction x is computed on a rectangular pixel array of width w and height h. Hence, the total number of pixels in the reconstruction is given by $n=wh$. Let d be the total number of available LR images. For each LR image, we assume that the number of pixels is l. The total number of available LR pixels is denoted by $m=ld$. The entries of the $n\times 1$ column vector x correspond to the pixel values of the reconstruction. The $m\times 1$ column vector y contains the LR image pixels, ordered column-wise. Finally, the $m\times n$ system matrix W defines the transformation from x to y.

Ignoring noise, the reconstruction problem can then be formulated as a system of linear equations (see, e.g., Chapter 7 of [9]):

$$Wx = y. \tag{3}$$

An (approximate) solution of (3) can be found using an iterative algebraic reconstruction method such as ART, SART, or SIRT [9]. In our experiments, we used SIRT to compute a solution for which the norm of the difference $\|Wx-y\|$ between the computed set of LR pixels and the measured data is minimal w.r.t. a certain vector norm, i.e., a least-squares solution.

B. *Simultaneous Iterative Reconstruction Technique*

In this section, we will give a brief overview of SIRT with application to the reconstruction of a HR, from a small number of LR images as well as the motion estimation method that we are used.

C. *The Principle of SIRT*

SIRT was introduced in the field of computed tomography (CT), where an image needs to be reconstructed from a set of X-ray projection images [8]. However, in our research it has been used to reconstruct a HR image from a set of LR images based on the described system model in (3). Let $x=[x_j]$ represent a high resolution image that we want to reconstruct from a set of low resolution images that denote by $y=[y_j]$. Let $W=[w_{ij}]$ denote the system matrix that connects the two. Furthermore, let $R=[r_{ij}]$ and $C=[c_{ij}]$ be diagonal matrices of inverse row and column sums of the system matrix, respectively; that is, $r_{ii}=1/\sum_j W_{ij}$ and $c_{jj}=1/\sum_i W_{ij}$. This leads to the following compact SIRT update expression:

$$x^{(k+1)}=x^{(k)}+CW^{T}R(y-Wx^{(k)}). \tag{4}$$

As noted by others, e.g. [10] [11] then SIRT solves a weighted least-squares problem, namely $\|Wx-y\|$. For a detailed review, we refer to [12].

D. *Motion Estimation within SIRT*

To reconstruct a HR image from a set of LR images, knowledge of the transformation W between the HR image and each of the LR images is crucial. To estimate the shift with subpixel accuracy, phase correlation is often employed, which uses the fast Fourier transform (FFT) of the shifted LR images to obtain a measure of correlation [13] [14] [15]. In our work, a more general approach is employed to estimate the transformation parameters, by integrating the estimation of the transformation between the HR image and the LR images within the proposed iterative reconstruction scheme (shown in Fig. 1). The motion estimation procedure is as follows:

1) Initialize the transformation parameters (an initial estimate for the shift can be obtained using the cross-power spectrum as in [2]).
2) Reconstruct a HR image from the set of measured LR images using the estimated transformation parameters.
3) Simulate the LR images from the reconstructed HR image by geometrically transforming the HR image to the grid of each of the LR images and subsequently blurring and downsampling the transformed images
4) Compute the mean squared error (MSE) between the acquired LR images and the simulated LR images
5) Find new estimates of the transformation parameters by minimizing the mean squared error (MSE) between the acquired LR images and the simulated LR images as a function of the transformation parameters
6) Go to step 2 until a certain convergence criterion is reached.

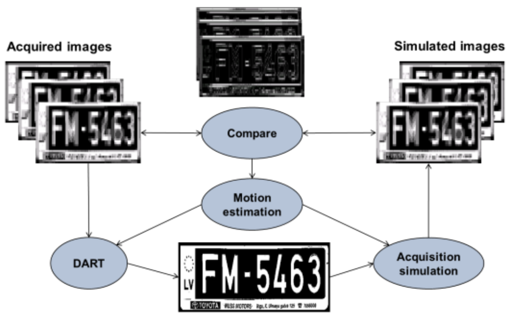


Figure 1. Motion parameter estimation within SIRT

III. Experiments and Results

Simulation experiments were set up to test the performance of the proposed license plate reconstruction methodology. For the experiments, two high resolution images were created, one binary HR image and one color HR image, both of size 1024*256, shown in Fig. 2(a) and Fig. 2(b), respectively. Furthermore, a HR real license plate picture was captured with a simple digital camera (Fig. 2(c)). The HR real image was of size 69×449 pixels captured by a digital camera (Canon PowerShot A480). One pixel of the HR image corresponded to a physical dimension of 0,98 mm. From this image, a set of LR images was created by scaling, shifting, blurring, and subsequently downsampling the HR image. The blurring involved a convolution of a Gaussian kernel of size 5×5 with a standard deviation equal to 2 times the HR pixel width. The weights of the kernel are computed by the value of the Gaussian function in the center of each pixel in the kernel. Next, from the set of simulated LR images, a HR image was reconstructed using SIRT.

For each experiment described below, the reconstruction quality of SIRT was calculated in terms of the root-mean-squared (RMS) error. The RMS was computed as the root of the sum of squared differences between the original HR image and the reconstructed HR image, divided by the total number of HR pixels.

(a) HR binary image

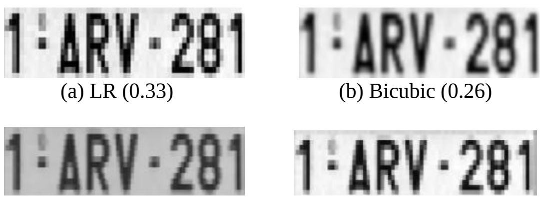
(b) HR color image

(c) HR real image

Figure 2. High resolution license plates used as test images

First, the performance of SIRT was compared to that of bicubic interpolation, Robust SR and a Fast Robust SR method suggested by Farsiu et al. [16]. For this comparative experiment, we used 15 LR images of size 15*109 pixels, generated from Fig. 2(c). The HR image shown in Fig. 2(c) was used as the ground truth image. The results of the employed reconstruction methods are presented in Fig. 3, along with their RMS error. Fig. 3(a) shows one of LR images. Fig. 3(b) is the result after bicubic interpolation (by averaging the interpolated LR images). Next, the reconstructed image using the Fast Robust SR and Robust SR method are shown in 3(c) and 3(d) respectively. The selected parameters for the Robust SR method were as follows: λ=0.04, P=2, β=1, α=0.7 and where the bicubic interpolated image was used as the input estimate. Finally, Fig. 3(e) shows the result of SIRT.

In both iterative methods, 40 iterations were employed. These images show that SIRT yields the best results, both visually and in terms of the RMS error.



(a) LR (0.33) (b) Bicubic (0.26)

(c) Fast Robust SR (0.24) (d) Robust SR(0.22)

(e) SIRT (0.11)

Figure 3. Comparison of different methods along with their RMS error; 3(a) One of the LR images; 3(b) Bicubic interpolation; 3(c) Fast Robust SR, 3(d) Robust SR [14]; 3(e) SIRT;

E. Reconstruction Performance : SIRT in Experimental Conditions

In this section, the performance of SIRT as a function of (simulated) experimental conditions will be discussed such as the number of LR input images and the pixel size of the LR images of size 15*109 pixels.

F. Number of LR Images

Each LR image generally provides new information that can be used in the reconstruction. It is intuitively clear that the quality of the HR image reconstruction should improve with the number of LR images. Fig. 4 shows the RMS as a function of the number of LR images used in the reconstruction. For this experiment, the number of iterations for SIRT was 100. For blurring, a 9×9 Gaussian kernel was used with width 2 HR pixels. The LR images were randomly shifted and the shift was assumed to be known. Fig. 4 shows that with only a small number of LR images, already a significant improvement in reconstruction quality can be obtained. We remark that the contribution of each LR image to the reconstruction quality depends on its shift with respect to the grids of the other LR images. It is clear that, when this shift is an integer times the size of the LR pixel, no additional information is added. However, since in practice, the time sampling of the LR images is independent of the spatial sampling, this is unlikely to occur.

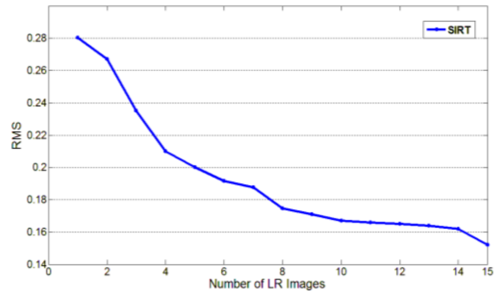
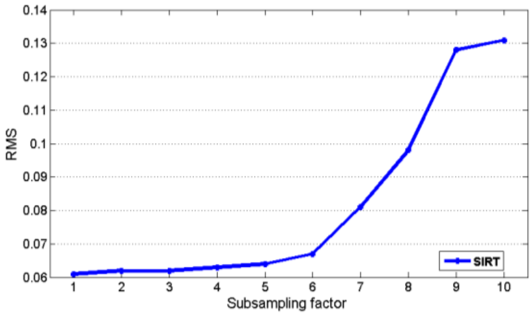


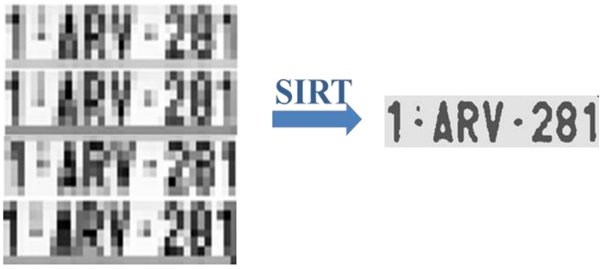
Figure 4. RMS error as a function of the number of LR images

G. Subsampling Factor of the LR Images

The subsampling factor of LR images is naturally of importance with respect to the quality of the reconstructed HR image. In this experiment, the RMS of SIRT as a function of the subsampling factor that used to generate the LR images was considered. To this end, 10 sets of LR images were used in which each set contained 4 LR images with the same subsampling factor. The blurring kernel was 5*5 with a Gaussian width of 2 HR pixels. For this experiment 40 iterations of SIRT was performed. Not surprisingly, it is clear from Fig. 5(a) that the RMS increases with increasing subsampling factor. However, considering the size of LR images that are very small for high subsampling factors (e.g. Size of LR images for subsampling equal to 8 was 7×35 pixel) and numbers that are hardly readable, the reconstruction quality of SIRT can be appreciated (see Fig. 5(b)).



(a)



(b)

Figure 5. (a) RMS error in function of the subsampling factor

(b) HR image reconstructed from 4 LR images of size 7×35

H. *Motion Estimation*

In practice, the transformation between the HR image and the LR images is unknown and needs to be estimated. As explained in Section *II.B.2*, the transformation parameters can be estimated within the reconstruction scheme. Conventionally, shifts are estimated based on phase correlation.

For this experiment a set of 5 LR images with random shifts was generated. Each LR image was of size 8 × 37 (e.g., Fig. 6(d)). The RMS error was computed from a SIRT reconstruction in which the shifts were known (Fig. 6(a)), from a SIRT reconstruction in which the shifts were estimated using cross correlation (Fig. 6(b)) and from a SIRT reconstruction in which the shifts were estimated using the proposed iterative method (Fig. 6(c)). The number of SIRT iterations was 40 for all experiments.

(a) RMS=0.12

(b) RMS=0.19

(c) RMS=0.16

(d)

Figure 6. Comparison of (a) a SIRT reconstruction with known shifts; (b) SIRT reconstruction with a priori estimated shifts using phase correlation and (c) SIRT reconstruction with shifts estimated during the reconstruction; (d) one of the 4 LR images.

I. *Color License Plates*

SIRT can easily be applied to the reconstruction of color license plates as well. Indeed, each band represents a grey level image with only very small grey levels. Hence, from the sets of LR images for each band, a HR image band can be reconstructed. After the reconstruction of the separate bands, the HR image is composed. An example is shown in Fig. 7, where 10 LR images were used with downsampling factor 8 in both directions and 50 iterations of SIRT were used.

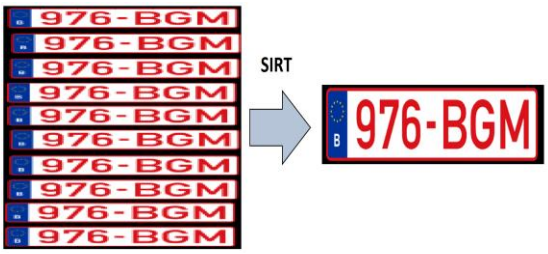


Figure 7. SIRT color license plate reconstruction from 10 LR images

IV. CONCLUSIONS

We have presented a new application of SIRT, an iterative algebraic reconstruction algorithm, for resolving a high resolution license plate image from a series of low resolution images. The SIRT algorithm benefits the efficiency of iterative algebraic methods from continuous tomography to compute accurate HR reconstructions from relatively few LR images.

Simulation experiments demonstrated that the SIRT algorithm is capable of computing reconstructions of high quality from a small number of LR images. The algorithm is very effective for binary images, but has also proved to be effective for reconstructing gray-scale and color images.

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