Super-Resolution Image Reconstruction using the Discontinuity Adaptive ICM

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Abstract

We propose a Bayesian approach for the super resolution image reconstruction (SRIR) problem using a Markov random field (MRF) for image characterization. SRIR consists of using a set of low-resolution (LR) images from the same scene to generate a high-resolution (HR) estimate of the original object. Using a Bayesian formulation, it is possible to incorporate previously known spatial information about the HR image to be estimated. In our approach, the iterated conditional modes (ICM) algorithm is used to find the maximum a posteriori (MAP) solution, and a discontinuity adaptive framework is used to overcome the oversmoothness inherent to MAP-MRF formulations. To evaluate the capability of the algorithm in reconstructing the actual image, we used the universal image quality index (UIQI). According to this index, the proposed method produced accurate results.

1. Introduction

SRIR consists of using several images of the same scene to find an estimation of the original object at a higher resolution grid. A review of the SRIR problem can be find in references [2] and [7]. In such context, all the observed LR images must have sub-pixel displacements among each other. Thus, the uncertainty inherent to the sub-pixel displacements can be used as additional information to increase the spatial resolution. In this paper, we first determine the relative sub-pixel displacements among the undersampled observations. Then, an initial estimate is constructed from the registration of all observations on a HR grid. Later, a discontinuity detection procedure is performed and the ICM algorithm was applied to find the MAP estimation of the image on a HR grid.

2. The Proposed Method

Following a lexicographic ordering, consider a HR image vector f of size $M^2 \times 1$. A set of LR versions of f can be given by

$$g_k = D_k H f + n_k \tag{1}$$

where g_k, $k = 1, \ldots, K$, of size $N^2 \times 1$, $N \leq M$, is a LR image vector and D_k of size $N^2 \times M^2$ is the down-sampling operator for the k-*th* observation. Following a more realistic approach, we assume that H is the $M^2 \times M^2$ block-circulant matrix that gives the blurring degradation effects from the optical system during the acquisition procedure and n_k models the noise. In equation (1), we are considering that all the observations were acquired by the same sensor, but at different positions. Thus, D_k is different for each of the K observed LR images g_k.

It is well known that SRIR is an ill-posed problem [7]. Thus, some kind of regularization is required to reach a good approximation of the original scene. Actually, we intend to find the MAP estimate $\hat{f}$, given the LR observations g_k, and the *a priori* probability distribution of f. The ICM algorithm can be used as a computationally feasible alternative in computing the MAP estimate [1]. This algorithm is based on equation (2) for the *a posteriori* probability of the value of the pixel i, given the vector g (which is constructed using all the observations) and the current values of all pixels in the neighborhood of the pixel i, f_{η_i}.

$$p(f_i|g, \hat{f}_{\eta_i}) \sim p(g_i|f_i).p(f_i|\hat{f}_{\eta_i}) \tag{2}$$

For our proposes, we assume that the conditional probability density function of the LR pixel given the HR one, $p(g_i|f_i)$, can be modeled by a Gaussian distribution, and that the actual image can be described by a Potts-Strauss model [6]. Thus, each HR pixel f_i depends on its neighbors f_{η_i}, given a neighborhood system η_i.

Image models based on a MAP-MRF formulation usually imply a uniform smoothness of the image. This oversmoothness does not respect discontinuities, where abrupt changes occur. According to Li [5], there have been strong research efforts on ways to apply the smoothness constraint while preserving discontinuities. Since Geman and Geman [3] introduced *line fields* to preserve edges, discontinuity adaptive methods have been applied to control the interaction between neighbors in such a way that when a discontinuity is detected, the degree of interaction is adjusted not to smooth the area. In our approach, an adaptive interactive function proposed by Li [5] is applied as a discontinuity detection procedure on the first estimate of the actual HR image. Thus, whenever a discontinuity occurs, the ICM algorithm diminishes the interaction between neighbors proportionally to the discontinuity intensity.

3. Results

We evaluated the proposed method in a simulated situation. Sixteen LR images with sub-pixel displacements between each other were generated according to the image formation model presented in equation (1). The actual HR Lena image (with 512x512 pixels) was convolved with a 3x3 uniform rectangular kernel to simulate a blur, due to an optical system. Furthermore, each LR image (with 128x128 pixels) was corrupted by additive and independent Gaussian noise at 40 dB. Figure 1(a) shows one LR observation and Figure 1(b) presents the result from the registration of all the LR observations on the HR grid. We have used the algorithm described in reference [4] for the sub-pixel image registration procedure. This image was used as the initial HR estimation for the ICM algorithm. For comparison purposes, Figure 1(c) presents the result of the bilinear interpolation of one LR observation and Figure 1(d) shows the reconstructed image using the proposed algorithm. For the numerical evaluation of the results, we adopt the UIQI proposed by Wang and Bovik [8]. This index varies from -1 to 1. We believe that this quality index is more appropriate to the SR context since it models distortions as a combination of three different factors: loss of correlation, luminance distortion, and contrast distortion. Table 1 shows the resulting quality indexes. The UIQI values are in agreement with the visual inspection of the images. In all the conducted experiments, the algorithm had a fast convergence rate, where less than 10 iterations were sufficient to produce good results. From Table 1 we note that the ICM algorithm, with the discontinuity adaptive method, performs better than the algorithm without the discontinuity adaptive procedure. We also note that the proposed method was able to produce similar results compared with the Irani-Peleg algorithm [2] that, for the best of our knowledge, it is the more accurate algorithm for SRIR in literature.

Registered Image	0.9660
ICM	0, 9331
Discontinuity Adaptive ICM	0.9875
Bilinear interpolation	0.9668
Irani-Peleg	0.9897

Table 1. UIQI for the HR reconstructed images.

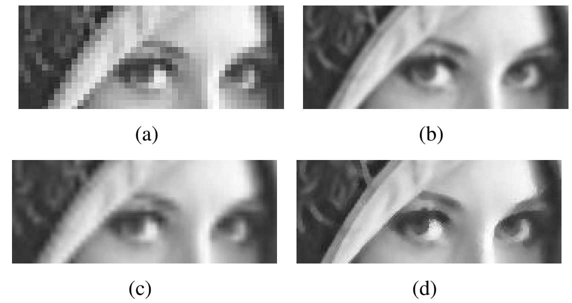

Figure 1. (a) a LR observation; (b) HR registred image; (c) bilinear interpolation; (d) HR image, reconstructed using the ICM algorithm.

4. Concluding Remarks

In this paper, we propose an algorithm for SRIR based on Markov random fields, where the ICM algorithm was used for computing the maximum *a posteriori* estimate. To overcome the uniform smoothness, inherent to the MAP-MRF formulation, the initially detected discontinuities were imposed in the estimation process using a discontinuity adaptive method. In future works, we intent to test the algorithm with other models for the *a priori* probability density function of the actual image.

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