Image and Vision Computing 26 (2008) 1277–1284

Contents lists available at ScienceDirect

Image and Vision Computing

journal homepage: www.elsevier.com/locate/imavis

Image magnification based on a blockwise adaptive Markov random field model

Xiaoling Zhang [a,b,c], Kin-Man Lam [a,*], Lansun Shen [b]

[a] Centre for Signal Processing, Department of Electronic and Information Engineering, The Hong Kong Polytechnic University, Hong Kong, China
[b] Signal and Information Processing Lab, Beijing University of Technology, Beijing, China
[c] Department of Communication Engineering, Xiamen University, Xiamen, Fujian, China

ARTICLE INFO

Article history:
Received 31 May 2006
Received in revised form 7 January 2008
Accepted 4 March 2008
Available online

Keywords:
Image magnification
MAP estimation
Markov random field
Iterated function systems

ABSTRACT

In this paper, an effective image magnification algorithm based on an adaptive Markov random field (MRF) model with a Bayesian framework is proposed. A low-resolution (LR) image is first magnified to form a high-resolution (HR) image using a fractal-based method, namely the multiple partitioned iterated function system (MPIFS). The quality of this magnified HR image is then improved by means of a blockwise adaptive MRF model using the Bayesian 'maximum a posteriori' (MAP) approach. We propose an efficient parameter estimation method for the MRF model such that the staircase artifact will be reduced in the HR image. Experimental results show that, when compared to the conventional MRF model, which uses a fixed set of parameters for a whole image, our algorithm can provide a magnified image with the well-preserved edges and texture, and can achieve a better PSNR and visual quality.

1. Introduction

In most electronic imaging applications such as scientific, medical and space systems, consumer electronics, and entertainment applications, images with a high resolution are desired and often required. A high-resolution (HR) image can not only give viewers a pleasing picture, but also provide additional details of the picture that are important for recognition and analysis in many applications. Given a low-resolution (LR) image, a magnification technique can provide a HR image with the visual contents of the original image preserved as much as possible, without changing the resolution of the image sensor.

To compute an estimate of the HR image of a given LR observation, the commonly used image magnification approaches are based on nearest-neighbor, bilinear, and bicubic interpolations [1,2]. The nearest-neighbor interpolation copies from the corresponding neighboring pixels to an empty location in a HR image, which tends to produce blocky images. The bilinear and bicubic techniques usually smooth an image in discontinuous regions, which then produce a HR image with a blurred appearance. Some non-linear interpolation techniques [3,4] have also been proposed to maintain edge sharpness in recent years. Other more sophisticated solutions to the magnification problems include the Bayesian maximum a posteriori (MAP) approach [5], wavelet-based approach [6,7], fractal-based approach [8–13], and PDEs-based approach [14,15].

The conventional fractal-based method causes serious blocky artifacts due to the independent and lossy coding of the range blocks. The MAP approach in [5] can preserve the edges in an image using the Huber-MRF prior model, which is a constrained optimization problem with a unique minimum. The Bayesian MAP estimation method is also very promising in image super-resolution technology [7,16–18]. Therefore, our proposed algorithm will magnify a LR image in the Bayesian MRF framework. However, the conventional MRF model used is usually characterized by a single set of fixed parameters. This cannot describe the whole image effectively, as natural images are usually inhomogeneous. Consequently, a conventional MRF model will often produce blocky or staircase artifacts at the edge regions. These artifacts will become much more serious when an image is magnified 4×4 (16) times or more.

Image magnification is an ill-posed problem, which can be solved using a Bayesian MAP framework with a probabilistic image model. This MAP approach can identify an optimal solution through the use of a prior image model. In other words, it can provide a flexible and convenient way to model prior knowledge. In this paper, we employ this approach to search for an optimal realization of the HR image given a LR image when the magnification factor is 16 or more, and we use the gradient-descent algorithm to compute the HR estimate. In addition, our MAP approach is different from the previous ones in the following two ways. First, although the MRF can provide a general model for images, the conventional MRF uses a single set of fixed parameters to model a whole image. Most of the parameter estimation methods for the MRF model are used for homogeneous images only, and the estimation of the parameters is usually computationally intensive. In

* Corresponding author. Tel.: +852 27666207.
E-mail addresses: zxl1@xmu.edu.cn (X. Zhang), enkmlam@eie.polyu.edu.hk (K.-M. Lam).

0262-8856/$ - see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.imavis.2008.03.003

order to apply the MRF model to characterize prior knowledge for image magnification, we propose a new, efficient parameter estimation method based on blockwise adaptive estimation. In our method, an initial estimated HR image is first divided into small blocks, and the parameters of the MRF model for each block are defined as inversely proportional to the energy in its corresponding direction. The particular MRF prior model is used to further regularize the estimated HR image in the next iteration. With this approach, we can avoid artifacts at the edges while retaining and enhancing sharpness in the HR images. Second, the initial HR image is calculated based on the multiple fractal codes, i.e. the multiple partitioned iterated function system (MPIFS) proposed in [13]. Using different range block partitioning schemes, a number of magnified images are generated, which are then averaged to obtain the initial HR image. The averaging process in the MPIFS method can remove the noise and preserve the edges well. In summary, our proposed method first employs the MPIFS to generate an initial HR image, whose quality is then improved by a regularization procedure with a block-based adaptive MRF model. Experiments show that our algorithm can produce HR images with significantly better visual quality and better PSNR quality than the conventional MRF-MAP approach can.

This paper is organized as follows. In the next section, we will present the LR image acquisition model and the Bayesian MAP analysis framework. In Section 3, we introduce the MRF prior model and describe our proposed parameter estimation method used for image magnification. Section 4 will give a brief introduction to the MPIFS magnification algorithm used for generating an initial HR image. Section 5 provides the implementation details of our algorithm in the MAP framework. Section 6 gives the experimental results, and Section 7 contains the discussion and conclusion.

2. LR image acquisition model and bayesian map approach

In this section, we will describe the LR image formation model from its HR version, and show how image magnification is an optimization problem that can be solved using the Bayesian MAP approach.

2.1. The LR image formation

Suppose that X represents the HR image of size $qN_1 \times qN_2$, and Y represents the corresponding LR image of size $N_1 \times N_2$, where q is the down-sampling factor in both the horizontal and vertical directions. If we consider the magnification of the LR observation Y to the HR image X, q will be called the zooming factor or the magnification factor. In this paper, the corresponding block of $q \times q$ pixels obtained by magnifying a pixel in the LR image is called a zooming block. In a LR image acquisition procedure, the point spread function (PSF) of the LR sensor is usually modeled by spatial averaging [5], so the LR image Y is related to its HR version X, as described by (1). Here, we assume that no noise is introduced in the acquisition process.

$$Y_{i,j} = \frac{1}{q^2}\left(\sum_{k=q\cdot i}^{q\cdot(i+1)-1}\sum_{l=q\cdot j}^{q\cdot(j+1)-1} X_{k,l}\right), \quad i = 0, \ldots, N_1 - 1; \quad j = 0, \ldots, N_2 - 1. \tag{1}$$

Eq. (1) defines the constraint of each pixel value $Y_{i,j}$ of the LR image, which should be equal to the average of the corresponding $q \times q$ pixels, i.e. the zooming block, in the HR image. The formulation (1) can be written in matrix form as follows:

$$Y = DX, \tag{2}$$

where D is the down-sampling matrix of dimension $N_1N_2 \times qN_1qN_2$, which generates aliased LR images. Since there is an infinite number of possible HR images X for a given LR image Y, the image magnification is therefore an ill-posed inverse problem in the sense of Hadamard [5,7]. A well-posed problem can be formulated using a stochastic regularization technique by means of the Bayesian MAP estimation; this results in a constrained optimization problem with a unique minimum using a variety of established techniques.

2.2. The maximum a posteriori (MAP) estimation

The MAP estimate is a statistical approach which has the appealing attribute of yielding the most likely image given the observed data. This approach can work very well with a variety of problems. Given a LR image Y, the MAP estimate of the HR image X is obtained by maximizing the following conditional probability density function $P(X|Y)$:

$$\widehat{X} = \arg\max_{X} P(X|Y). \tag{3}$$

Using the Bayesian rule and taking the logarithm of the a posteriori probability, (3) can be written as follows:

$$\widehat{X} = \arg\min_{X}\{-\log P(Y|X) - \log P(X) + \log P(Y)\}, \tag{4}$$

where $P(Y)$ is a constant because Y is the given LR observation, $P(X)$ is the image prior model, and $P(Y|X)$ is the probability of reconstructing the LR image Y given the HR image X. For noise-free cases, $P(Y|X)$ is also a constant. Therefore, the MAP estimate of the HR image is given as follows:

$$\widehat{X} = \arg\min_{X}\{-\log P(X)\}, \tag{5}$$

where X is the set of all images that satisfy the constraints. In the MAP optimization (5), the *a priori* knowledge represented by $P(X)$ provides a regularized HR image estimate. Thus, the specific choice of a prior distribution $P(X)$ is critical. The Markov random field (MRF) has the capability of representing different images and the context-dependent nature of each image, so it is adopted to model the HR images. As a matter of fact, the MRF has been widely used to model images in the Bayesian framework for characterizing a stochastic pattern or prior knowledge.

3. The MRF prior model and parameter estimation

It is well known that the neighboring pixels in an image tend to have a strong correlation to each other, as the intensity values of the pixels usually vary gradually, except in the boundary regions. The MRF is a popular approach used in image processing to reflect this property of smoothness. The joint distribution of an MRF is characterized by a Gibbs function with a set of clique potential parameters, where the parameters specify the weight of smoothness in an image [19]. Typically, these parameters allow the MRF prior model to be adjusted for the best performance. In this section, we will first present the MRF model, and then propose an efficient blockwise parameter-estimation method.

3.1. The Markov random field (MRF) model

In the 1920s, mostly inspired by the Ising model [20], a new type of stochastic process appeared in probability theory, namely the Markov random field (MRF). The use of MRF in image processing became popular after the work of Geman and Geman [21] on image restoration in 1984. The MRF theory provides a convenient and consistent way of modeling context-dependent entities such as image pixels and other spatially correlated features. The practical use of MRF models was largely ascribed to the equivalence between MRF and Gibbs distributions established by Hammersley and Clifford and further developed by Besag [22].