Digital Reconstruction Of Degraded Low Resolution Images

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Abstract— **Many imaging applications nowadays rely on digital image interpolation because they require much higher spatial image resolution than the camera sensors can produce. In this paper we present a novel method for interpolating digital images. Unlike other conventional interpolation methods, the unknown pixel value is not estimated based on its local surrounding neighbourhood, but on the whole image. In particularly, we exploit the repetitive character of the image. A great advantage of our proposed approach is that we have more information at our disposal, which leads to a better reconstruction of the (hypothetical) desired image and its high frequencies. Results show the effectiveness of our proposed method and its superiority to other traditional interpolation methods, especially with real images where one has to deal with image corruption such as noise and compression artefacts.**

Keywords—**image interpolation, super resolution, image reconstruction**

I. Introduction

THESE days more and more security firms are providing both public and private places with cameras to put up a vigorous fight against crime. However in order to recognize a face of the criminal or to read a license plate of the getaway car, we often need clean high resolution (HR) images. Unfortunately cheap camera sensors with low resolution are used massively nowadays in webcams, GSM's and surveillance cameras, which leads to many unsolved cases. The high cost for high precision optics and image sensors is therefore an important concern in many commercial applications regarding HR imaging.

On the other side, there is a limitation on increasing spatial resolution by reducing pixel size (i.e. increasing the number of pixels per unit area) by sensor manufacturing techniques. If the pixel size decreases, the amount of incoming light per pixel unit then also decreases. It generates shot noise that degrades the image quality severely.

In many situations, the images can not be re-recorded, e.g. in case of a robbery. If it comes to that, we need to extract the information as much as possible from the available images. Sometimes (important) additional information is obscured or even vanished during acquisition, so before reconstructing the HR image, we investigate a theoretical acquisition model as illustrated in figure 1.

General blur can be originating from the *point spread function* (PSF) of the sensor, optical systems (out of focus, diffraction limit, aberration, etc.) and even motion (due to the limited shutter speed). If the Nyquist criterion is not satisfied during downsampling, frequencies above half the sampling rate will be reconstructed and appear as frequencies below half the sampling rate. The resulting distortion is called aliasing, which hides additional information, i.e. the ideal high frequencies. Additive noise occurs within the sensor or during transmission.

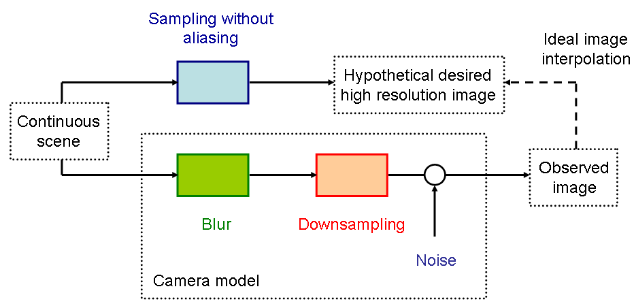

Fig. 1. Observation model of the image acquisition.

Additional image compression degrades the quality of the observed image even more, which makes the reconstruction more difficult. The biggest challenge is to invert or undo all these degrading processes as much as possible in order to obtain the clean ideal HR image.

In the following sections we will discuss our proposed image reconstruction scheme, show some results and draw a conclusion.

II. Our Proposed Reconstruction Scheme

Another class of upscaling methods which also takes advantage of repetitivity, is called *super resolution* (SR) reconstruction. SR is a signal processing technique that obtains a HR image from multiple noisy and blurred low resolution images (e.g. from a video sequence) [1]. Contrary to image interpolation, SR uses multiple source images instead of a single image.

It is often assumed that true motion is needed for SR, however many registration methods do not yield true motion: their results are optimal to some proposed cost criterion, which are not necessarily equal to true motion. With this in mind, we can hypothetically assume that repetitive structures could serve as multiple noisy observations of the same structure (after proper registration). Results of our experiments in §III will confirm that this hypothesis holds for real situations. Besides repetitivity in texture, we can also find this recurrent property in other parts of the image, e.g. in similar objects or along long edges.

We propose a simple interpolation method which exploits this repetitive behaviour. Our interpolation method is based on our theoretical camera model as shown in figure 1. Our scheme is quite straightforward and consists of three consecutive steps:
1. For the sake of simplicity, we define small rectangular win-

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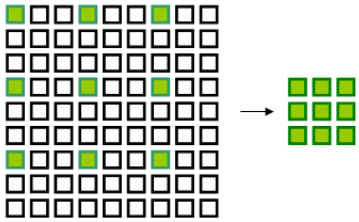

Fig. 2. The $3:1$ decimation operator maps a $3M \times 3N$ to an $M \times N$ image.

dows B (e.g. 5×5 pixels) as basic structure elements. We search for repetitive blocks in the whole image, which have a similar structural or geometrical content of the windows as well as similar luminance and colour information.

Afterwards we calculate the translational shifts on the HR grid between the interpolated reference block B and the zero-filled matched repetitive structures. In order to obtain accurate shifts, we interpolate the reference block using a fast non-linear restoration technique based on level curve mapping, which do not suffer from artefacts like blurring, staircasing and/or ringing as in traditional interpolation methods [2]. Zero-filling is the opposite process of the decimation operator (i.e. the downsampling operator in the camera model) as illustrated in figure 2.

2. Starting from the maximum likelihood principle, it can be shown that minimizing the norm of the residuals is equivalent to median estimation. A residual is the difference between an observed pixel value and the predicted pixel value. The median is very robust to outliers, such as noise and errors due to misregistration. For this reason we adopt the median estimate of all observations for every pixel in the HR grid for which we have at least one observation. For pixels with no observation, we borrow their values from the interpolated reference blocks. Since the original pixels contain the least noise, we also remap these pixels. In a nutshell, we have fused all repetitive structures robustly into one single image.

3. We assume that the blur in the camera model in figure 1 is characterized by a shift-invariant PSF. The inverse problem becomes highly unstable in the presence of noise. This can be solved by imposing some prior knowledge about the image. Typically we will try to force spatial smoothness in the desired HR solution. This is implemented as a penalty factor in the following robust minimization cost function:

$$\widehat{I}(\mathbf{x}) = \arg\min_{\mathbf{I}(\mathbf{x})} \left[|\nabla \mathbf{I}(\mathbf{x},\mathbf{t})| + \lambda \left| \mathbf{H} * \mathbf{I}(\mathbf{x},\mathbf{t}) - \mathbf{I}(\mathbf{x},\mathbf{0}) \right| \right] \quad (1)$$

where H denotes the PSF-kernel (typically Gaussian blur) and λ is the regularization parameter between the two terms, respectively called the regularization term and the data fidelity term. Image $I(\mathbf{x},\mathbf{0})$ is the noisy blurred HR image.

The use of the so-called edge-stopping functions (e.g. the total variation used in equation 1) in the regularization term is very popular, because it suppresses the noise better while retaining important edge information [3]. We use the L_1-norm function for the data fidelity term because we could assume that the outliers are better modeled by a Laplacian probability density function (PDF) rather than a Gaussian PDF according to [1].

III. Experiments And Results

As a first realistic experiment we have both printed and scanned one A4 paper containing the *Lorem ipsum* text with the HP PSC 2175 machine at 75 dpi as shown in figure 3. The Lorem ipsum text is very popular as default model text, but additionally it has a more-or-less normal distribution of letters [4].

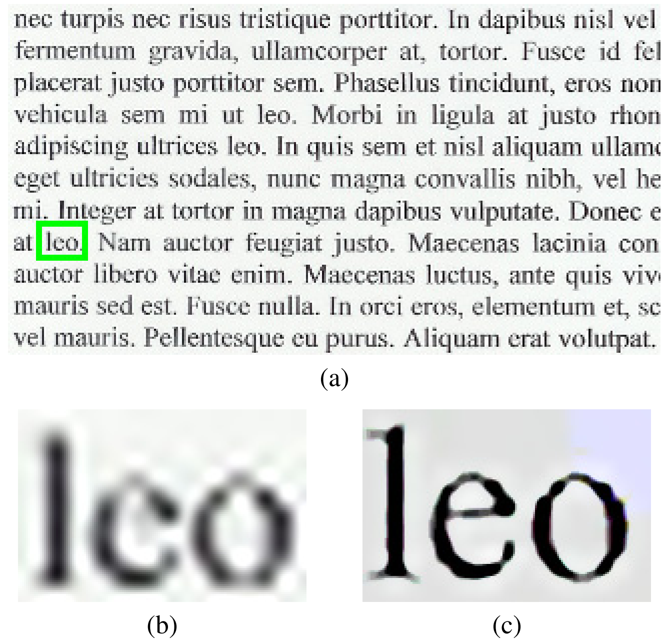

Fig. 3. Interpolation of the Lorem ipsum text ($8\times$ enlargment): (a) a part of the original scanned text image (at 75 dpi), (b) cubic B-spline interpolation, (d) our proposed method.

We can clearly see in figure 3 that our method outperforms a traditional interpolation technique (used in commercial software): the characters are much better readable and reconstructed, noise and JPEG-artefacts are heavily reduced and much less blurring, staircasing and ringing artefacts are created.

IV. Conclusions

In this paper we have presented a novel interpolation scheme based on the repetitive character of the image. Exploiting repetitivity brings more information at our disposal, which leads to much better estimates of the unknown pixel values. Results show the effectiveness of our proposed interpolation technique and its superiority at very large magnifications to other interpolation methods: details are reconstructed well and artefacts are heavily reduced.

References

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