Evaluation the Application of Image Processing and Digital Signal Processing

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Abstract: The main purpose of this study is evaluation the application of image processing and signal processing in various scientific field such as computer science and astronomy and biometry. Besides, Super-resolution (SR) technique reconstructs a higher-resolution image or sequence from the observed LR images. Signal Processing has evolved into Digital Signal Processing (DSP) allowing computer simulations and digital electronics implementations. Today, it's difficult to consider DSP algorithms without their software implementation and/or a proper dataset. Technical details are discussed in this article, including optimization algorithms, parameter selection methods, reconstruction models and acceleration strategies. It's suggested an objective quality meter for quantifying the combined blackness and blurriness distortions in frequency domain.

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1. Introduction

SR is a technique which reconstructs a higher-resolution image or sequence from the observed LR images. Technically, SR can be categorized as multi-frame or single-frame based on the input LR information. If multiple images of the same scene with sub-pixel misalignment can be acquired, the complementary information between them can be utilized to reconstruct a higher-resolution image or image sequence, as Fig. 1 shows. However, multiple LR images may sometimes not be available for the reconstruction, and thus we need to recover the HR image using the limited LR information, which is defined as single-frame SR.

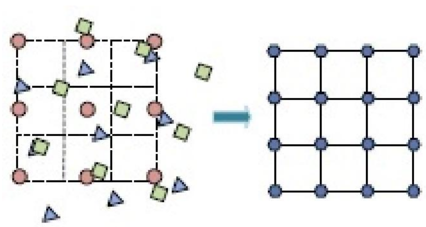


Fig. 1. The concept of multi-frame super-resolution.

The grids on the left side represent the resolution enhancement is therefore still necessary, especially in fields such as video surveillance, medical diagnosis, and remote sensing applications. Considering the high cost and the limitations of resolution enhancement through "hardware" techniques, especially for large-scale imaging devices, signal processing methods, which are known as super-resolution (SR), have become a potential way to obtain high-resolution (HR) images. With SR methods, we can go beyond the limit of the low-resolution (LR) observations, rather than improving the hardware devices.

LR images of the same scene with sub-pixel alignment, thus the HR image (the grid on the right side) can be acquired by fusing the complementary information with SR methods. Although SR techniques have been comprehensively summarized in several studies, this paper aims to provide a review from the perspective of techniques and applications, and especially the main contributions in recent decades.

This paper provides a more detailed description of the most commonly employed regularized SR methods, including fidelity models, regularization models, parameter estimation methods, optimization algorithms, acceleration strategies, etc. Moreover, we present an exhaustive summary of the current applications using SR techniques, such as the recent Google Skybox satellite application and unmanned aerial vehicle (UAV) surveillance sequences. The current obstacles for the future research are also discussed.

Literature Review:

Nowadays, charge-coupled devices (CCDs) and complementary metal oxide semiconductors (CMOSs) are the most widely used image sensors. To obtain an HR image, one of the solutions is to develop more advanced optical devices. As the spatial resolution is governed by the CCD array and optical lens, reducing the pixel size is one of the most direct approaches to increase the spatial resolution. However, as the pixel size decreases, the amount of available light also decreases, and the image quality becomes severely degraded by shot noise. Furthermore, nonrectangular pixel layouts, as in the hexagonal Fujifilm super CCD and the orthogonal-transfer CCD, have been used to increase the spatial sampling rate, as shown in Fig. 2. Other approaches include increasing the focal length or the chip size. However, a longer focal length will lead to an increase in the size and weight of cameras, while a larger chip size will result in an increase in capacitance. Therefore, both of these approaches are not considered to be effective due to the limitations of the sensors and the optics manufacturing technology [4]. Compared with CMOSs, CCDs have advantages in sensor sensitivity, imaging resolution, noise suppression and technology maturity.

However, considering the high cost of current CCD-based cameras, CMOS-based technologies have recently been investigated. For example, Scientific CMOS (scoops) sensors feature a higher resolution and high signal-to-noise ratio (SNR); however, the practical use of this technology remains a problem. Overall, due to the limitations of hardware technology, it is still necessary to study SR algorithms to achieve the goal of resolution enhancement.

Based on the concept of SR, the first problem we need to discuss is the conditions to obtain an HR image from multiple LR observed images. In general, if there is supplementary information among the images, SR is feasible. That is to say, the LR observations cannot be obtained from each other by a transformation or resampling process, thus they contain different information which can be used for SR.

If the relative shifts between the LR images are integral, the images after motion registration will contain almost the same information. As a result, SR cannot obtain effective results.

To implement SR in a real application, researchers have attempted to acquire the images for SR through hardware control. By means of designing the imaging mechanism by hardware techniques, the sensors can acquire observations with known sub-pixel displacements, or multiple "looks" for the same scene. SR is therefore possible. Successful examples can be found in various fields. One of the most famous successful cases is in the field of remote sensing. In the French space agency's SPOT-5 satellite system, a specially developed CCD detector was used which packages two 12000-pixel CCDs in one structure. Two line-array CCDs are shifted with each other by half a pixel width in the line-array direction, as shown in Fig. 2.

For the calculation of blockings or blurriness index, the image is divided into blocks for block processing. The reason for block processing is that if we apply the FFT on whole image without block processing, then the chances of error is very high because the distortion might not be consistent and equal in every part of the image so the distortion is computed for each block locally and will be accumulated in the end as a single quality metric. The size 32x32 is chosen because the block size should be multiple of 8 (as DCT block size is 8x8) and the harmonics must have some distance among them to be recognized as harmonics that is why 32x32 window size is selected.

Since the two CCD detectors can capture images at the same time, a set of data can therefore be acquired at a half-pixel shift in the imaging position. Using this device and SR techniques, we can obtain a HR image from the two sub-pixel shifted images. Leica ADS40 aerial cameras have adopted a similar imaging mechanism to SPOT-5. Moreover, some CCD pixels comprise sub-pixels with different shapes and spatial locations. By combining multiple images recorded with different sub-pixel components, we can obtain a higher-resolution image via SR.

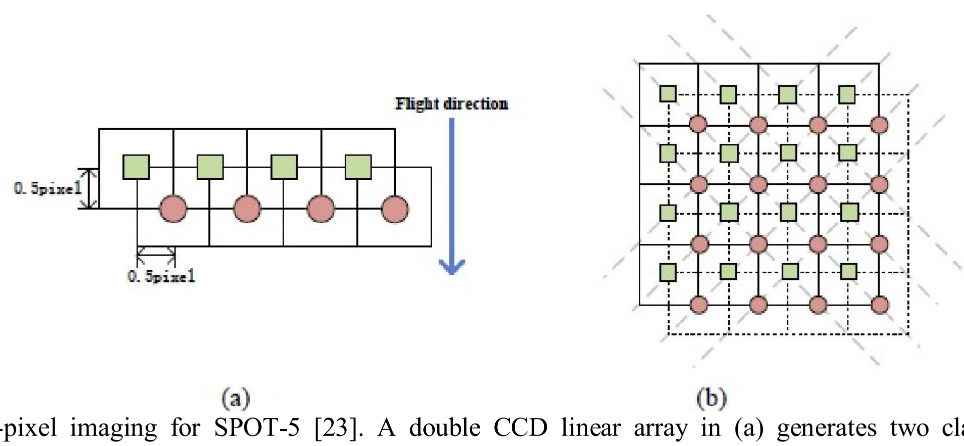


Fig. 2. Sub-pixel imaging for SPOT-5 [23]. A double CCD linear array in (a) generates two classical square sampling grids in (b), shifted by half a sampling interval in both row and column directions.

Super-resolution technologies and methods

In this part, we discuss the methods and current problems for SR with multiple observations. The key problem is how to use the supplementary information among the acquired repeat-pass images. In 1964, Harris established the theoretical foundation for the SR problem by introducing the theorems of how to solve the diffraction problem in an optical system. Two decades later, Tsai and Huang first addressed the idea of SR to improve the spatial resolution of Landsat TM images.

The main emphasis of this paper is to develop a distortion meter with combined blockings and blurriness distortions. Only blockings meter is not good in estimating quality of lightly compressed image (very little blockings) therefore adding a blur meter will help to compensate for that weakness. In the following parts the combined blackness and blurriness quality meter which is designed for full reference (FR) mode is explained. It consists of 3 main parts; 1) blockings estimation; 2) blurriness estimation and 3) combining the two distortions.

Since then, many researchers have begun to focus on SR, either in theoretical research or practical applications. SR has now been developed for more than three decades, and the progress of SR can be roughly summarized as follows.

At the very start, most of the methods concentrated on the frequency domain. Frequency domain algorithms can make use of the relationship between theHR image and the LR observations based on a simple theoretical basis, and have high computational efficiency. However, the methods have apparent limitations, such as sensitivity to model errors and difficulty in handling more complicated motion models, which have prevented them from further development.

Due to the drawbacks of the frequency domain algorithms, spatial domain methods then became the main trend. The popular spatial domain methods include non-uniform interpolation, iterative back-projection (IBP), projection onto convex sets (POCS), the regularized methods, and a number of hybrid algorithms. Early review papers have provided specific descriptions and explanations of those methods. Among them, the regularized methods are the most popular due to their effectiveness and flexibility.

Therefore, most of the recent representative articles about SR have focused on regularized frameworks. In this part, our emphasis is to review the development of the regularized methods, especially over the last decade.

Edge detection is used to determine the sharp luminance edges from the reference image. These sharp luminance edges are either due to the blockings artifact introduced in coding process or due to the textual details present in reference image. This spatial activity of both, reference and coded images, are determined by using sober edge detectors. The edge detection is performed horizontally and then vertically on both images.

Furthermore, the related research progress into parameter setup and optimization algorithms is also summarized. The remainder of this part is structured as follows.

Firstly, we talk about the imaging models. The related models are then described, including the data fidelity and regularization terms. Some advanced techniques and challenges are then discussed, including adaptive parameter setup, blind reconstruction, and optimization strategies.

The observation model

The imaging model, which refers to the observation model, is essential to SR when using a regularized framework. Before reconstruction, we need to clarify the process by which the observed images have been obtained. The image acquisition process is inevitably confronted with a set of degrading factors, such as optical diffraction, under-sampling, relative motion, and system noise. In general, we usually suppose that the degradation procedure during image acquisition involves warping, blurring, down-sampling, and noise, and the observation model is simulated as follows:

$$y_k = O_k D_k B_k M_k z + n_k \quad (1)$$

$$y_k = H_k z + n_k \quad (2)$$

The model in (1) is still insufficient for expressing all possible situations. As a result, other models take more complicated factors into consideration to better describe real cases, including different kinds of noise, dimensional complexity, domain transformation for the particular images, etc. These models are not discussed in detail in this paper.

Regularized reconstruction methods

Based on the observation model described above, the target is to reconstruct the HR image from a set of warped, blurred, noisy, and under-sampled measured images. As the model in (2) is ill-conditioned, SR turns out to be an ill-posed inverse problem.

Based on maximum a posteriori (MAP) theory, the problem we need to solve can be transformed to the minimization problem as:

$$E(z) = \arg\min_z \sum_{k=1}^{K} \rho\left(y_k - H_k z\right) + \lambda U(z) \quad (3)$$

The regularization term

The regularization plays a significant role in the regularized vibrational framework. As SR is a classical ill-posed inverse problem, regularization is therefore adopted to stabilize the inversion process. According to the Bayesian theorem, the regularization term represents the image prior modeling, providing the prior knowledge about the desired image. Over the past 10 years of vigorous development, there have been a large amount of studies of regularization for image restoration and SR.

Smoothness prior models

In the early years, the smoothness of natural images was mainly considered, which leads to the quadratic property of the regularizations. Tikhonov-based regularization is the representative smoothing constraint, whose energy function is usually defined as:

$$U(z) = \|\Gamma z\|_2^2 \quad (4)$$

To overcome the shortcomings of the TV prior model, some researchers have proposed spatially adaptive strategies. A number of methods use spatially adaptive regularization parameters to eliminate the staircase effects. Some of them classified the image into detailed and flat regions using the spatial information, and used a larger penalty parameter for the flat regions and a smaller one for the edges. However, the spatially adaptive indicators such as gradients, the difference curvature, and structure tensor are usually sensitive to noise.

To understand the combination strategy of blockings and blurriness artifacts we have to study their behavior and appearances in the images. As the compression ratio is increased, images tend to lose their higher frequency contents, due to their smaller energy they carry and appear blurry. This means, blockings is an ultimate consequence of blurriness. Once the blockings starts appearing, it means the image has already gone through the blurriness artifact and the blurriness is saturated. By further compressing the image, blockings artifacts starts appearing and it becomes dominant on blurriness artifact and user starts observing blockings in image. Finally for the combination of two distortions, more weightage should be given to blurriness at low compressions and at higher compression rates to blockings. The following graphs for blurriness and blockings weighting functions are estimated based on tests on various images of the data base.

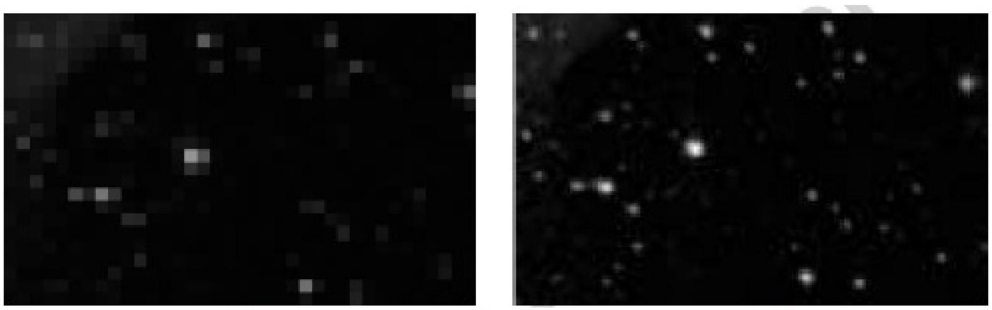
Nonlocal-based priors

The local derivatives are somewhat sensitive to noise in the images' homogenous regions, which negatively affects the reconstruction effect in noisy cases. Recently, the concept of nonlocal-based priors has been proposed and has developed rapidly in image processing. Rather than defining the neighborhood of a pixel locally, nonlocal-based priors consider pixels in a large search area and weight them according to the similarity between rectangular patches. This is based on the assumption that every feature in a natural image can be found many times in the same scene. The nonlocal models have become popular in the regularized framework, given the nonlocal TV regularization as:

$$U_{NLTV}(z) = \sum_{x\in\Omega} \sum_{y\in\Pi_x} w(x,y)\left|z(x) - z(y)\right| \quad (5)$$

Astronomical observation

The physical resolution of astronomical imaging devices limited by system parameters also provides a chance for SR techniques to play a role. Astronomical systems can typically collect a series of images for SR. By improving the resolution of astronomical images, SR can help astronomers with the exploration of outer space. A specific example is shown in Fig. 3 showing the SR of multiple star images.



(a) (b)

Fig. 3. SR example of astronomical images: (a) the original LR image, and (b) the SR result.

Satellites are also now being sent into outer space, e.g. the lunar exploration program and the Mars Odyssey mission and indicates an SR example of Chinese Chang'E-1 lunar images, where the result was reconstructed based on three views. The SR can enhance the image resolution, and thus improve the discernibility of small objects on the moon's surface. Beyond this, Hughes and Ramsey used Thermal Emission Imaging System (THEMIS) thermal infrared and visible datasets from different spectral regions to generate an enhanced thermal infrared image of the surface of Mars.

Biometric information identification

SR is also important in biometric recognition, including resolution enhancement for faces, fingerprints, and iris images. The resolution of biometric images is pivotal in the recognition and detection process. To deal with the LR observations, a common approach is the development of high-quality images from multiple LR images. Based on the redundancy and similarity in the structured features of biometric images, example-based single-frame SR with an external database is an effective way of resolution enhancement. We give three cases of biometric image reconstruction in Fig. 4. Using SR, the details of the shapes and structural texture are clearly enhanced, while the global structure is effectively preserved, which can improve the recognition ability in the relevant applications.

(a) (b) (c)

Fig. 4. The SR results for face, fingerprint, and iris images [189], respectively.

The first row is the LR image, while the second row shows the reconstructed result. (a) Face hallucination, (b) fingerprint reconstruction, and (c) iris reconstruction.

Discussion and conclusions

In this article, we intended to convey the concept, development, and main applications of super-resolution (SR) over the past three decades. The main progress in SR techniques can basically be divided into three stages. In the first decade, researchers shifted their attention from the study of frequency domain methods to spatial domain algorithms. Regularized multi-frame SR framework were the main focus in the second stage. The Bayesian MAP framework became the most popular technique due to its good performance and flexible characteristics. In recent years, however, the development of multi-frame SR has slowed down, and researchers have mainly focused on SR reconstruction in the various application fields. Unfortunately, the extensive practical use of SR still remains a problem. There has been a bottleneck-style dilemma in the development of multi-frame SR, while example-based SR for single images has become a hot issue. However, the performance of these algorithms depends on the reliability of the external database.

So what should we do in further studies? More advanced, adaptive, and faster methods with extensive applicability are always desirable. In addition, methods should be closely combined with actual requirements. The rapid development of hardware devices will also bring new challenges to the application of the SR framework. For instance, the Google Skybox project will provide us with an opportunity to obtain real-time HR "earth-observation videos" using remotely-sensed image SR. The concept of SR has also been extended to related fields such as fluorescence microscopy and multi-baseline tomographic synthetic aperture radar (SAR) imaging. Moreover, researchers have attempted to apply the single-frame SR techniques to the processing of medical and remote sensing imagery. However, the practicability of these methods is still limited by the time consumption, and acceleration strategies are essential for large-scale applications. In conclusion, the future of SR is still in our hands.

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