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A Study on Super-Resolution Image Reconstruction Techniques

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Abstract

With the rapid development of space technology and its related technologies, more and more remote sensing platforms are sent to outer space to survey our earth. Recognizing and positioning all these space objects is the basis of knowing about the space, but there are no other effective methods in space target recognition except orbit and radio signal recognition. Super-resolution image reconstruction, which is based on the image of space objects, provides an effective way of solving this problem. In this paper, the principle of super-resolution image reconstruction and several typical reconstruction methods were introduced. By comparison, Nonparametric Finite Support Restoration Techniques were analyzed in details. At last, several aspects of super-resolution image reconstruction that should be studied further more were put forward.

Keywords: Super-resolution, de-noising, image reconstruction, analytic continuation

1. Preamble

As the space technology develops faster and faster, we alow-resolutioneady have many platforms flying above our earth. Recognizing and positioning these space objects is often before knowing the earth. Additionally, as human beings explore the space and realize the danger of planetoid, we need to know more about the outer space, not only for our curiosity but also for our safety. Super-resolution image reconstruction is a new effective method to detect all the space objects. And through this technology, we can generate images that are near or even surpass diffraction limit, which can help a lot in space objects recognition. On the other hand, super-resolution images are inherently identical to remote sensing images, so some of the technologies in super-resolution image processing are also useful in remote sensing image processing. In 1991, B.R.Hunt applied this method to astronomical image reconstruction and put forward PMAP algorithm, which is based on maximum Poisson posterior estimate. 1995, B.R.Hunt pointed out that reason we can reconstruct super resolution image is there are high frequency information in low frequency components. Recent years, more and more researchers focus their studies on super-resolution image reconstruction and gain satisfying results in practice. In this paper, the principle of super-resolution image reconstruction is introduced and commonly used methods in super-resolution reconstruction are analyzed.

2. Basis of super-resolution

2.1 Definition of Super Resolution

Non-coherent transfer function of an optical system is the autocorrelation of its pupil function, which means that the transfer function is necessarily band-limited. In another way, the value of transfer function should be zero when frequency determined by diffraction limit is above certain value. Apparently, de-convolution can only restore the spectrum of object to diffraction limit and cannot surpass it. However, by using Fourier transformation, we can get resolution above diffraction limit in theory. The restoration technology which is trying to restore the information above diffraction limit is called Super-resolution techniques. And the methods used in these techniques can be called Extrapolation of Band-limited. Diffraction limiting Images of space objects can be obtain through high-resolution restoration of speckle images of these objects. But, with super-resolution information, resolution can be improved further by restoration and reconstruction of near-diffraction-limit images.

2.2 Theory

Super-resolution image reconstruction is based on the theory of Analytic Continuation, which means reconstruction of the whole analytic function according to its values in certain area. Because of diffraction of lights, spectrum distribution of certain image is infinite in space and optical system truncates its frequency to obtain frequency-truncated image that is finite in space. Generally, truncation function cannot be band-limited, but a diffraction limited optical system's truncation is band-limited, therefore, the reconstruction of whole spectrum function or just spectrum function above certain frequency is possible.

2.3 Classification of Techniques

There are a number of different algorithms developed to perform super-resolution reconstruction. These include non-uniform interpolation, frequency domain, deterministic and stochastic regularization, projection onto convex sets (POCS), hybrid techniques, optical flow, and other approaches

2.1.1 Non-uniform Interpolation

The basis of non-uniform interpolation super-resolution techniques is the non-uniform sampling theory which allows for the reconstruction of functions from samples taken at non-uniformly distributed locations. super-resolution image enhancement is a logical application of this new theory, but one that requires very accurate registration between images. Early super-resolution applications used detailed camera placement to allow for accurate interpolation. A new method was developed to overcome the limitations of insufficient registration accuracy by employing multiple digital sensors with different pixel sizes. This ensures that pixels of multiple images will not coincide regardless of camera placement. Non-uniform interpolation is a basic and intuitive method of super-resolution and has relatively low computational complexity, but it assumes that the blur and noise characteristics are identical across all low-resolution images.

2.1.2 Frequency Domain

Tsai and Huang proved that in the absence of noise or blurring it is possible to reconstruct a high-resolution image from multiple low-resolution images based on the aliasing present in the low-resolution images. This was accomplished by relating the aliased discrete Fourier transform coefficients of the low-resolution images to a sampled continuous Fourier transform of an unknown high-resolution image. Kim and Bose extended this to blurred and noisy low-resolution images; provided the noise has zero mean and the blur and noise are identical across all low-resolution images. This was accomplished using a recursive implementation based on the weighted least square theory

2.1.3 Regularization

Super-resolution image reconstruction is generally an ill posed problem. However, it can be stabilized with a regularization procedure. By assuming that registration parameters are estimated, the inverse problem can be solved by deterministic regularization by taking proper prior information about the solution. In this method a smoothness constraint is used as priori knowledge for reconstruction. An iterative regularized approach increases the resolution of a video sequence. A multiple input smoothing convex functional is defined and used to obtain a globally optimal high resolution video sequence. Current research is focused on simultaneous blur identification and robust super-resolution.

2.1.4 Projection Onto Convex Sets

Low resolution images usually suffer from blurring caused by a sensor's point spread function (PSF) and additionally from aliasing caused by under-sampling. Stark and Oskoui have proposed a POCS technique that accounts for both the blurring introduced by the sensors as well as the effects of under-sampling. An estimate of the high-resolution version of the reference image is determined iteratively starting from some arbitrary initialization. Successive iterations are obtained by projecting the previous estimate onto the consistency set with an amplitude constraint set that restricts the gray levels of the estimate to the range [0, 255].

2.1.5 Optical Flow

Some applications can benefit from the generalization of super-resolution techniques to support the imaging of objects that are non-planar, non-rigid, or which are subject to self-occlusion when rotated. One such application is super-resolution reconstruction of facial images. Baker and Kande present optical flow as a solution to this problem. Zhao and Sawhney present a comparison of three different flow methods: least-squares based flow, consistent flow (CONS), and bundled flow with CONS flow as initial input. They demonstrated that it worked well when small amount of noise were present, but that it was very sensitive to flow accuracy

2.1.6 Generative Methods

One example of the recent work in generative methods, that is, methods that use additional information not contained in the low-resolution image set to restore a high-resolution image, is the "reconstruction" research conducted by Baker and Kanade. Where earlier papers used smooth a priori assumptions, this technique relies on strong class based priors to provide far more information than simple smooth priors used in existing super-resolution algorithms. They claim significantly better results both in subjective and root-mean-square (RMS) pixel error. However, the use of strong class based priors' means that the method will find what it is looking for even if it does not exist in the image set. For instance, applying this method with face priors, but to a low-resolution scene of a grove of trees, will yield a face like image. An open research area is how these priors will effect applications such as face recognition that depend mainly on differences in a set of images that all fit the prior.

3. Comparison of super-resolution techniques

Comparisons of super-resolution techniques have been primarily concerned with what assumptions are made in the modeling of the super-resolution problem. Some of these assumptions include assuming the blurring process to be known or that regions of interest among multiple frames are related through global parametric transformations. Other models take into account arbitrary sampling lattices, a digital sensor elements physical dimension, a non-zero aperture time, focus blurring, and more advanced additive noise models. Many times these assumptions are chosen to simplify a model and are usually biased toward a particular method. In addition, methods that do not make these assumptions have not demonstrated objectively that removing these assumptions yields better super-resolution reconstruction performance. Signal-to-noise ratio (SNR), peak signal-to noise ratio (PSNR), RMS, mean absolute error (MAE), and mean square error (MSE) have all been used as objective measures of super-resolution accuracy; however, the prominent method of presenting results is clearly subjective visual quality.

4. **Conclusion**

The researches on super-resolution image reconstruction mainly only consider the situation that degraded model is linear and noise is neglected and systemic analyzing method and filter designing method have not been formed yet. As different methods of super-resolution have been developed using models with unequal assumptions of the underlying problem, and because the results provided have been primarily based on subjective measurements, it is difficult to find an unbiased comparison on what super-resolution methods are more appropriate for a given task. Most papers on super-resolution implementations provide subjective results by comparing the super-resolution image to a bilinear interpolated image or the source high-resolution image from which the low-resolution images were created. This does not provide a clear method of comparing different implementations suitability for a desired application.

5. Future work

We propose developing an objective measurement for comparison of super-resolution methods. One possible objective measurement is a universal image quality measures for human vision systems and computer vision systems. An alternative would be to use the high-resolution images as the input to some other image processing system, such as a face-recognition algorithm, and examine how different super-resolution techniques affect the recognition accuracy. Three research areas promise improved super-resolution methods:

5.1.1 Motion Estimation:

Super-resolution enhancement of arbitrary scenes containing global, multiple independent motion, occlusions, transparency etc. is a focus of super-resolution research. Achieving this is critically dependent on robust, model based, sub-pixel accuracy motion estimation and segmentation techniques presently an open research problem. Motion is typically estimated from the observed under-sampled data the reliability of these estimates should be investigated. Simultaneous multi-frame motion estimation should provide performance and reliability improvements over common two frame techniques. For non-parametric motion models, constrained motion estimation methods which ensure consistency in motion maps should be used. Regularized motion estimation methods should be utilized to resolve the ill-posedness of the motion estimation problem. Sparse motion maps should be considered. Sparse maps typically provide accurate motion estimates in areas of high spatial variance exactly where super-resolution techniques deliver greatest enhancement. Reliability measures associated with motion estimates should enable weighted reconstruction. Global and local motion models, combined with iterative motion estimation, identification and segmentation provide a framework for general scene super-resolution enhancement. Independent model based motion predictors and estimators should be utilized for independently moving objects. Simultaneous motion estimation and super-resolution reconstruction approaches should yield improvements in both motion estimates and super-resolution reconstruction.

5.1.2 *Degradation Models:*

Accurate degradation (observation) models promise improved super-resolution techniques reconstructions. Several super-resolution techniques application areas may benefit from improved degradation modeling. Only recently has color super-resolution techniques reconstruction been addressed. Improved motion estimates and reconstructions are possible by utilizing correlated information in color bands. Degradation models for lossy compression schemes (color sub-sampling and quantization effects) promise improved reconstruction of compressed video. Similarly, considering degradations inherent in magnetic media recording and playback are expected to improve super-resolution techniques reconstructions from low cost camcorder data. The response of typical commercial CCD arrays departs considerably from the simple integrate and sample model prevalent in much of the literature. Modeling of sensor geometry, spatio-temporal integration characteristics, noise and readout effects promise more realistic observation models which are expected to result in super-resolution techniques reconstruction performance improvements.

5.1.3 Restoration Algorithms

The Maximum A-Posteriori (MAP) and POCS based algorithms are very successful and to a degree, complimentary. Hybrid MAP/POCS restoration techniques will combine the mathematical rigor and uniqueness of solution of MAP estimation with the convenient a-priori constraints of POCS. The hybrid method is MAP based but with constraint projections inserted into the iterative maximization of the a-posteriori density in a generalization of the constrained MAP optimization. Simultaneous motion estimation and restoration yields improved reconstructions since motion estimation and reconstruction are interrelated. Separate motion estimation and restoration, as is commonly done, is sub-optimal as a result of this interdependence. Simultaneous multi-frame super-resolution restoration is expected to achieve higher performance since additional spatio-temporal constraints on the super-resolution image ensemble may be included. This technique has seen limited application in super-resolution reconstruction.

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