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Design & Development of an Image Super-Resolution Scheme

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Abstract:

Super-resolution aims to provide a high-resolution image from a group of one or additional low-resolution images by convalescent or inventing plausible high-frequency image content. Typical approaches try to reconstruct a high-resolution image using the sub-pixel displacements of many low-resolution images, typically regularized by a generic smoothness prior over the high-resolution image space. Different ways use training data to learn low-to-high-resolution matches, and are highly successful even in the single-input-image case. Here we tend to present a domain-specific image prior in the form of a p.d.f. based upon sampled images, and show that certainly types of super-resolution problems, this sample-based prior gives a significant improvement over other common multiple-image super-resolution techniques.

Keywords: Java, Image, Zoom, Color, Brightness, Contrast.

1. Introduction:

The consistent development of engineering in recent years has led to a growing interest in image restoration theory. The main directions are untraditional treatments to the classic problem and looking at new, second-generation restoration issues, allowing for more complicated and more computationally intensive algorithms. Among these new second generation issues area unit multiple image restoration and super resolution image restoration. This project focuses on the latter downside of super resolution restoration. Application of such restoration ways arises within the following areas.

1. Remote sensing: - where several images of the same area are given, and an improved resolution image is sought.

2. Frame freeze in video: - Where typical single frame in video signal is generally of poor quality and is not suitable for hard-copy printout. Enhancement of a freeze image can be done by using several successive images merged together by a super resolution algorithm.

3. Medical imaging (CT, MRI, ultrasound, etc.):- These enable the acquisition of several images, yet are limited in resolution quality.

The super resolution restoration idea was first presented by Tsay and Huang. They used the frequency domain approach to demonstrate the ability to reconstruct one improved resolution image from several down sampled noise-free versions of it, based on the spatial aliasing effect. Other results suggested a simple generalization of the above idea to noisy and blurred images. A frequency domain recursive algorithm for the restoration of super resolution images from noisy and blurred measurements is suggested. A spatial domain alternative, based on Papoulis and Yen generalized sampling theorems is suggested by Ur and Gross. Srinivas and Srinath proposed a super resolution restoration algorithm based on a minimum mean squared error (MMSE) approach for the multiple image restoration problem and interpolation of the restored images into one. All the above super resolution restoration methods are restricted to global uniform translational displacement between the measured images, linear space-invariant (LSI) blur, and homogeneous additive noise.

Super-Resolution is a multithreaded Image project. Super-resolution is an image fusion and reconstruction problem, wherever an improved resolution image is obtained from many geometrically warped, low resolution images. The HR image isn't only an image that has additional pixels (like in the case of interpolation), however it also has additional visible details. A non-iterative technique of image super-resolution based on weighted median filtering with gaussian weights is projected. Visual tests and basic edges metrics were used to examine this method. it was shown that the weighted median filtering reduces the errors caused by inaccurate motion vectors. Image re sampling is one in every of the foremost vital issues in image process. Despite the rise of the resolution of recent camera sensors, this downside continues to be actual, for instance, for previous low-resolution video information and it's important for police investigation applications. Several pictures re sampling algorithms use cloister info. As Associate in nursing example, image self-similarity at totally different resolutions is employed in NEDI algorithmic rule. However this approach improves the image visual quality given that the a priori info is true.

2. Literature Review:

Super Resolution (SR) is the process of combining a sequence of LR images in order to produce an image or sequence of higher resolution. Following are the literature survey for image super resolution.

1) From the earliest algorithm proposed by Tsai and Huang, 12 super-resolutions have attracted a growing interest as a purely computational means to increase imaging sensors performance. It is unrealistic to assume that the super resolved image can recover the original scene O(x, y) exactly. A reasonable goal of the SR is a discrete version of O(x, y). Which has high spatial resolution than the resolution of the LR images and which is free of the volatile blurs (de convolved)? In the paper, we will refer to this super resolved image as the HR image of f (i, j) and the ratio between the size of the sought HR image and input LR image will be called a SR factor. The standard SR approach consists of sub pixel registration, overlaying LR images on an HR grid and interpolating the missing values. The sub pixel shift between images thus constitutes an essential feature.

2) Research on intrinsically MBD methods has begun fairly recently The MBD methods can directly recover the blurring functions from the degraded images alone. We further developed MBD theory in 7 by proposing a blind de-convolution method for image. Which might be mutually shifted by unknown vectors? To make this brief survey complete, we shouldn't forget to mention a very challenging problem of shift-variant blind de convolution.

3) A countless number of papers address the standard SR problem. A good survey can be found for example in. Most super-resolution methods fall into one of the following four categories: frequency domain, projection onto convex set (POCS), Maximum a Posteriori (MAP) and 2-step, scattered interpolation followed by deblurring, methods. Frequency domain method were historically the first developed. They are based on the shifting property of the Fourier transform and the assumption that the original HR image is band limited. This application is largely restricted to cases where only translational motion is present, limiting considerably their use in many practical scenarios. From the plethora of the SR algorithms proposed we focused this survey study in two alternative approaches that have been analyzed in depth by the authors: 1) BSR method and 2) Neural-network based method.

4) The next surveyed method in this work is a two-step learning-based super-resolution technique. The algorithm is based on the application of scattered-point interpolation on projected sequence data, followed by a filtering operation to restores degradations associated to sequence pixel size and residual errors introduced by interpolation. This scattered point interpolation module has been implemented using novel hybrid neural network architecture and enabling the processing of synthetic sequences to learn optimum distance-based interpolation functions for different noise

levels in the input sequences. The restoration process is carried out by application of an optimum linear filter operation to the scattered-point interpolated image. The filter coefficients, which are assumed to be rotationally symmetric, which have been determined by minimizing on synthetic data the squared differences between high-resolution images and restoration of first-step interpolated images.

5) Experimental results showed significant improvements, both in visual and RMS error terms, over Wiener filter restorations adapted only to correct lens and detector degradations. As in two-step methods in general, this super-resolution scheme implicitly assumes that all sequence frames are affected by the same space-invariant degradation, which is caused exclusively by LR optics and detector blurs and have a same noise level. Being targeted to achieve near real-time SR execution on input imagery of best quality, in particular no provisions are made to try to identify and restore the effect of common degradations such as those caused by defocus or movement blur. To perform this operation will requires in general the design of a super-resolution algorithm that integrates a blind de convolution operation. In this work, the performance of this two-step super resolution method, with performance equal or better than classical MAP super resolution methods, is evaluated on real image sequences with respect to a state of the art BSR method that integrates a blind de convolution step, to better understand the role played by de convolution on the global quality provided by super-resolution methods.

3. Problem Definition:

As the space technology develops faster and faster, we already 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. As a research hotspot, Nonparametric Finite Support Restoration Techniques are studied in details.

Noncoherent transfer function of an optical system is the autocorrelation of its pupil operate, i.e. the transfer function is necessarily band-limited. in different way, the value of transfer function should be zero when frequency determined by diffraction limit is for certain value. Apparently, deconvolution will only restore the spectrum of object to diffraction limit and can\'t surpass it. By using Fourier transformation, we will get resolution on top of diffraction limit in theory. The restoration technology, which is trying to restore the information on top of diffraction limit, is called Super-resolution techniques and therefore the methods used in these techniques are called Extrapolation of Band-limited.

4. Objective:

In this project, we present a new approach toward the Super resolution restoration problem. Simplicity and direct connection to the problem of single image restoration (from one measured image) are the main benefits of this approach. Thus, the various known methods to restore one image from one measured image are easily generalized to the new problem of single image restoration from several measured images. We start our presentation with a new model to the problem and then turn to apply known restoration methods to the suggested model. Modeling the Problem The key to a comprehensive analysis of the classical super resolution problem is to formulate the problem and to model it as simply and as efficiently as possible. We start by presenting the problem to be solved and then turn to introduce an analytical model describing it.

Throughout this project we represent images column wise lexicographically ordered for matrix notation convenience. A hybrid algorithm is proposed that combines the benefits of the simple ML estimator (maximum-likelihood estimation (MLE) is a method of estimating the parameters of a statistical model), and the ability of the POCS to incorporate non ellipsoids constraints (use of force to prevent). This hybrid algorithm solves a constrained convex (curving or bulging outwards) minimization problem and combining all the a priori knowledge on the required result into the restoration process. An efficient iterative 2-phase algorithm is presented for solving the defined problem, and convergence (the occurrence of two or more things coming together) is assured to the optimal point. Simulations are performed to demonstrate super resolution restoration using the hybrid algorithm. An interesting question with regard to super resolution restoration is raised and treated in this paper. Typically, super resolution restoration methods assume that motion exists between the measured images. The question whether the motion is necessary for super resolution restoration ability is not treated in the literature. We demonstrate that, indeed, there is an ability to restore an image with improved resolution, based on several motionless-blurred, decimated and noisy image.

1. Introduce, into the modeling of the super-resolution from low resolution image sequences, the blurring function of the procedure and a function that is unknown in real problems.

2. Study image models, both general and aimed at improving the images of concrete objects, For example faces, license plates, texts, cars, military vehicles, aircrafts, ships and installations that appear in images of surveillance and security.

3. Jointly address the estimation of the image, the displacement vectors and also the blurring function or functions under the Bayesian problem formulation.

4. Get into the estimation method, additionally to point estimates of the image, motion and blur function. Probability distributions of those estimators that allow their simulation.

5. Deploy in a friendly graphical user interface based on all algorithms that are developed in the project so they is used by researchers and company. Apply the results to real images provided by the companies interested in the project.

The main objective of this software tool is that the implementation of several super-resolution techniques. in particular, Multi-Dimensional Signal processing (MDSP) and several references therein are included. This techniques implemented cover robust ways, dynamic color super-resolution ways and simultaneous demosaicing and resolution enhancement.

Some specific features of the software packages are:

1) As part of this software package, motion estimation is done automatically by the program, or independently estimated motion vectors may be provided by the user.

2) The user is able to specify the region of interest to be processed.

3) A basic tracking algorithm is incorporated in the program so that if only a certain part of the input images are important for the user (a car moving in a crowded street), this region can be tracked and another data sequence containing only that particular object is produced.

4) The parameters of the imaging system (such as the point-spread function) may be specified by the user.

5) The input image files may be given as .mat (Matlab data file) or .avi format.

6) The output generated by the program can be .mat (Matlab data file) or .avi format.

7) Producing color or grayscale output images are optional, given color input frames.

8) The project can handle arbitrary-sized stacks (low resolution 2D input images) and 4D hyper stacks (low resolution 3D input images).

9) Multithreading (user can choose the number of computational threads).

10) Gauss-Newton used as a non-linear solver.

11) Different output types (i.e. source, Byte, Short or Float).

12) Single and double precision.

13) Show iterations option.

14) Non-modal GUI.

5. Methodology:

i) Type of Study:

In this section the two steps of a neural network based super-resolution method are described. In the first step, scattered-point interpolation is performed on projected sequence data using a neural network architecture that learns from examples optimum distance-to-weight interpolation functions for several input sequence noise levels.

The second step restores on the interpolated image the combined degradations due to low-resolution optics and detector blurs as well as residual degradations due to the interpolation procedure. The restoration filter coefficients are obtained by application of a learning process on a set of synthetically generated sequences, for which the super-resolution result is available. Despite the simplicity of the method, which allows a near real-time implementations, the use of optimum coefficients for both steps of the process enables to obtain results of quality equal or better than classical MAP super-resolution methods, with a reduction in computation time by a factor of almost 300. The reader is referred to38 for implementation and evaluation details concerning this method.

ii) Area of Study:

In a traditional framework, sampling theory is concerned with the problem of re- constructing a signal from its samples. However perfect reconstruction schemes are rarely available for highly complex signals like a real-world scene: it is not possible to acquire a low-resolution image and have it displayed on a high resolution screen without inevitably introducing undesirable visual artifact. One solution to overcome this problem is provided by the technique of super-resolution. Developing new accurate registration techniques that can improve image super-resolution algorithms was the initial and main motivation throughout this research.

We thus implemented an image super-resolution algorithm that incorporates the proposed feature extraction techniques in the registration part. With the local and the global features, the super-resolved images obtained from artificial data showed an improvement of the quality, both visually and in terms of PSNR, when com- pared to the super-resolved images obtained with the same implementation but using standard feature extraction methods. These results emphasize the need for very precise registration methods for super-resolution.

Given these favorable results, we then ran real experiments of image super- resolution from images acquired by a real camera. To satisfy our model, simple calibration measurements of intrinsic parameters of the camera, like the point-spread function, were carried out and the notion of polyphase components of an image was used for registration. The obtained super-resolved images from real data set show a real improvement in their resolving power compared to the acquired images.

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Besides, this also underlines the fact that the proposed image acquisition framework is appropriate for modeling existing cam- eras.

Finally, the last super-resolution experiment was conducted without prior calibration and the settings were chosen in order to obtain the best super-resolved image possible. Along the same line as the sampling theory for FRI signals, the work presented in this thesis on new feature extraction techniques takes into account the inherent defects and imperfections of an acquisition device like cameras and turns these shortcomings to an advantage. Similarly to where aliasing was exploited to provide more information, it is here the knowledge of the sampling kernel that allows to develop exact methods for extracting features almost irrespectively to original resolution of the acquired signal.

iii) Universe and Sample:

In the scattered-point interpolation phase, sequence pixels are projected on the HR image frame, and image values at the grid nodes are estimated using a scattered-point interpolation technique. This projection operation requires the knowledge with accuracy higher than the input pixel size of the geometrical transforms that link sequence frames. In this method, we have used to this end a sub-pixel registration procedure based on an iterative gradient descent method which, in turn, is a development based on the Lucas-Kanade registration procedure.

Using this registration mehod, sub-pixel accurate mappings are computed between the sequence frame selected as reference and the rest of frames within the sequence. The coordinate system of the HR image is taken aligned to that of the reference system, so that pixels in both images are related by a simple scaling operation.

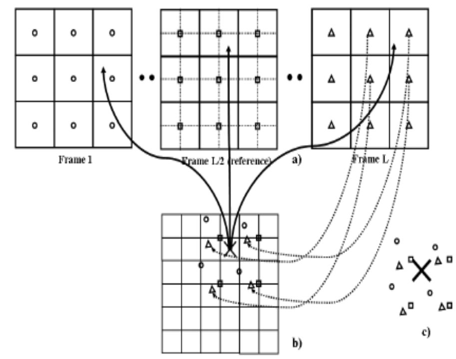

Diagram of the interpolation procedure: a) Sequence frames, with the central frame selected here as reference; b) projection of a HR grid node (zoom x2 in this example, aligned to the reference frame) onto the sequence frames, and retro-projection of first-order neighborhoods around the projected node location; c) image values at HR grid nodes are estimated by scattered-point interpolation of the retro-projected image values.

Using these mappings, we are able to project a node of the HR grid onto any sequence frame, and the four first-order neighbors of the projected position in the frame low-resolution (LR) rectangular grid can be subsequently identified. Retro-projecting these neighbors onto a common coordinate frame, such as the one defined by the reference frame and performing this process over the entire sequence, we obtain an irregular cloud of LR image samples that encircle each node of HR grid. Using these samples, the image value at the HR node is estimated using a scattered-point interpolation procedure. A diagram of the interpolation procedure is depicted in figure . The scattered-point interpolation is carried out using a modification of the probabilistic neural network (PNN), a neural architecture introduced by Specht.41 The PNN is a multivariate kernel density estimator with fixed kernel width. This method is closely related to a non-parametric regression technique, the Nadaraya-Watson estimator,44 and to probability density estimation methods, such as the Parzen windows method.

A diagram of the proposed neural architecture is presented in figure 2. The network estimates the image value at a HR grid node as a weighted average of the pixels that constitute the first-order neighborhoods of the projected node location at the different sequence frames.

iv) Data Collection & Proposed Tools:

In this section, we consider the case of image super-resolution from real images using the samples as they are acquired by a digital camera. The registration approach considered here is based only on the continuous moments. Since the registration approach takes a sampling point of view, we want our image samples to be modified as little as possible by internal post-processing occurring in a digital camera after acquisition. The set of images is thus acquired by a SLR digital camera (Nikon D70s) in RAW format with no edge sharpening. In a first experiment, pictures are taken in a classroom. The focal length is set at 18mm (35mm equivalent: 27mm) and other settings are: F16, 1/60s and ISO 200.

To estimate the support and the shape of the PSF, the slanted edge method is used. The PSF is the response of an imaging system to an infinitely small point light source. Measuring it directly can thus be very difficult. The slanted edge method estimates the PSF indirectly by measuring the Edge Spread Function (ESF). It requires a picture of a slanted step edge to be taken so that the sampling rate of the step edge is increased.

By differentiating along the edge's normal direction, the Line Spread Function (LSF) can be obtained (the response of the camera to a single line). The LSF represents the cross- section of the PSF in a given direction. The PSF is assumed to be circularly symmetric and spatially invariant in the considered region, so that only one LSF is necessary to characterize the PSF. An implementation following ISO standards for java of the slanted edge method

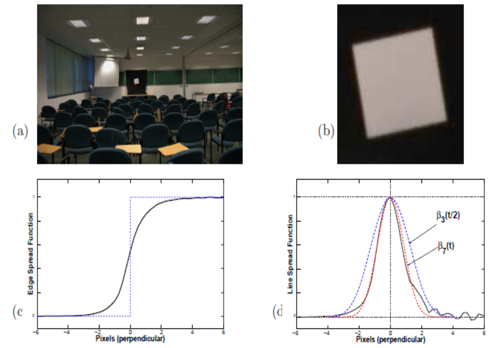

Fig : Estimation of the PSF with the slanted Edge Method; (a) Image of a slanted white square with step edges for Point Spread Function estimation (acquired with a Nikon D70s digital camera); (b) Zoom on the target; (c) Measured Edge Spread Function (solid line) and ideal step edge (dashed line); (d) Measured Line Spread Function (solid line). Its support has length 8 ranging from -4 to 4. The sampling t) can be modeled for example by either a centered B-spline of degree 7, β7 (t) (dashed line) or a centered B-spline of degree 3 scaled by 2, β3 (t/2)(dash-dot line). In both case, the sampling kernel has support 8.

Results of the estimation of the PSF are presented in Figure. The acquired image is presented in Figure (a) and the target for the PSF estimation is shown in Figure (b). The measured ESF is the solid line in Figure (c) while the estimated LSF is the solid line in Figure (d). From both functions, it can be observed that the support of the PSF is approximately 8 pixels, ranging from -4 to 4. The bell shape of the PSF is fitted with a B-spline of support as well. Two different fits are presented in Figure (d): a B-spline of degree 7, β7 (t) (dashed line), and a B-spline of degree 3 scaled by 2, β3 (t/2) (dash-dot line). Although β7 (t) seems to fit better the measured LSF, both functions are considered.

v) Data Analysis & Techniques:

The first experiment shows the main characteristics of the BSR method. Fig 8 shows a frame sequence taken from the Vanderwalle dataset. It is worth to mention that in the LR frames (Fig. 1a) a significant amount of spectral aliasing is

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present. We will take advantage of such aliasing to recover high frequencies in the HR frames. Fig 1c shows the edge information taken as the prior by the BSR method to regularize the solution. Fig.1d shows that this method is able to provide the PSF of each frame as a byproduct.

The next example corresponds to a frame sequence from the Farsiu&Milanfar database18 †. Fig. 2a shows one of the original"eia" frames and Fig. 2b shows the BSR result. For the next example, we took a Olympus C5050Z digital camera and captured 4 photos, registered them with cross correlation and cropped each to 70x40 pixels (Fig. c). Fig. d shows BSR result. A potential pitfall that we have to take into consideration is a feasible range of SR factors. As SR factor increases we need to take more LR images and the stability of BSR decreases. Hence we limit ourselves SR factor between one and 2.5 in most practical applications.

The second group of experiments illustrates the influence of the number of iterations in the reconstruction provided by the BSR technique. We have taken the"alpaca" dataset from the Farsiu & Milanfar database and reconstructing the HR frames for different iterations (Fig. 10). It turns out that the best reconstruction results appear for a reduced number of iterations (2 in this particular example). This result can be corroborated both visually and also using a non-reference metric proposed by the authors in.56 A similar response was observed in the "castle" example illustrated in Fig. 8.

A third experiment shows the performance of the MLP-PNN method fig3. Presents the reconstruction results after applying the first and second step of the described method and includes a comparison with a bicubic interpolation method. A final group of experiments provides a comparative study of the performance of different SR methods. Here is left to the reader to decide which method provide the best reconstruction quality

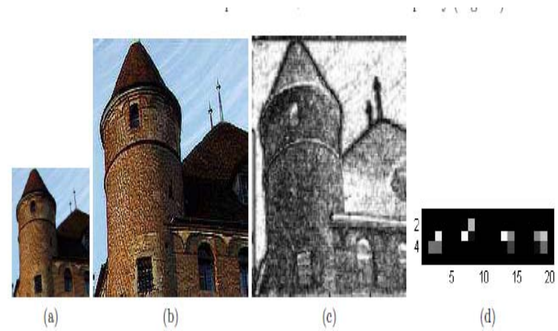

Figure 1: (a) Shown is one of 4 LR frames. Frame sequence was taken from Vanderwalle dataset55. Note the presence of aliasing in the brick structure of the tower (b) The BSR result (c) Image of the prior edge information used by the BSR method; (d) PSF of each frame estimated by the BSR method.

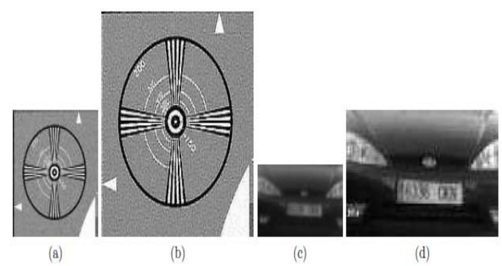

Figure 2: (a) Shown is one of 4 LR frames. Note the presence of aliasing in such frames as in the previous example. Frame sequence was taken from Farsiu&Milanfar"eia" dataset; (b) The BSR result. (c) Shown is one of four LR frames taken by F.S. from a real traffic sequence (d) BSR result

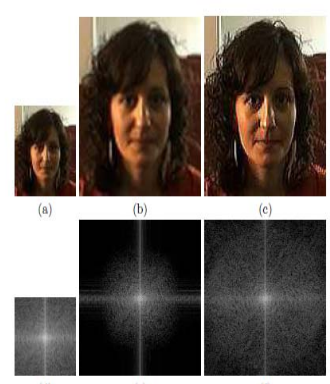

Figure 3: Superresolution a color video sequence (a) Shown is one LR frame taken with a webcamera (b) Interpolated result (c) BSR result (d)

Magnitude of the FFT of (a) (e) Magnitude of the FFT of (b). Note the loss of high frequencies, (f) Magnitude of the FFT of (c). Note how the BSR technique is able to recover the high frequency part of the spectrum.

6. Application:

1) Medical imaging (i.e. CAT, MRI etc).

2) Satellite imaging.

3) Enlarging Consumer Photographs.

4) Video Surveillance (i.e. Car wash kidnapping).

5) Converting NTSC video content to high definition television.

7. Limitation:

The main problem that limits the robustness of most of the SR methods are due to the presence of high compression rates which still are omnipresent in most of the video surveillance scenarios. Very recently Pham has noted that de convolution is found ineffective by irreversible DCT quantization what produces annoying blocking artifacts after compression. The next experiment we are interested to analyze the impact of the introduction of different levels of compression in the test sequences. We have taken the Farsiu & Milanfar ”car” sequence and saved as JPEG format through the java command in write for different quality levels. Fig. 2 shows that for a compression quality of 80% or lesser the reconstruction artifacts using the BSR method become unacceptable.

8. Significance of the Study:

This project addresses the super resolution restoration problem: Namely, given a number of moved, blurred and noisy versions of a single ideal image, one wants to restore the initial image. To solve this problem, a brand new general model was introduced. This model enabled the direct generalization of classic tools from restoration theory to the new problem. In this context, ML, MAP and POCS methods are all shown to be directly and simply applicable to super resolution restoration with equivalencies between these methods. The restoration problem at hand in every of those approaches reduces to the problem of solving a very large set of sparse linear equations.

We have presented in this thesis new feature extraction methods for the registration of multiview images. The proposed techniques allow the exact extraction of the considered features and are very efficient for image features that are acquired at low resolution. The problem of feature extraction was formulated as a multichannel sampling problem for which results from the sampling theory for signals with finite rate of innovation were considered. The main requirement necessary to use this theory is that the characteristics of the acquisition device, like the sampling kernel, must be known in advance or through a preliminary calibration procedure. The sampling kernel assumed in the major part of this thesis are B-spline functions which exhibit appealing properties (compact support, reproduction of polynomial, dual basis) as well as being suitable for modeling real camera devices.

The new sampling schemes for FRI signals have been first extended to a multi- channel acquisition setup and, depending on the assumed sampling kernel (polynomial- or exponential-reproducing one), their performances in this new framework have been analyzed. It appears that kernels reproducing polynomials are not suitable for a truly distributed and symmetric multichannel setup and requires an asymmetric setup. Experiments of distributed acquisition of bilevel polygons have been carried out and, although they are somewhat artificial and mostly for illustration purposes, some applications can be WE have presented in this thesis new feature extraction methods for the registration of multiview images. The proposed techniques allow the exact extraction of the considered features and are very efficient for image features that are acquired at low resolution. The problem of feature extraction was formulated as a multichannel sampling problem for which results from the sampling theory for signals with finite rate of innovation were considered. The main requirement necessary to use this theory is that the characteristics of the acquisition device, like the sampling kernel, must be known in advance or through a preliminary calibration procedure. The sampling kernel assumed in the major part of this thesis are B-spline functions which exhibit appealing properties (compact support, reproduction of polynomial, dual basis) as well as being suitable for modeling real camera devices.

9. Conclusions:

In this paper, we have established a gradient profile prior for natural image. Using this prior, a gradient field constraint is enforced for the problem of image superresolution.

The gradient constraint helps to sharpen the details and suppress ringing or jaggy artifacts along edges.Encouraging results are obtained on a variety of natural and synthetic images.

Noisy LR image is denoised by non-local denoising method , then the denoised image is up-sampled by the proposed method, and the noises are up-sampled by bilinear interpolation.

For noisy input LR image, estimating the gradient profile might be inaccurate due to the noise. One possible solution is to denoise the LR image first, then add the up-sampled noises back after the image super-resolution In the future, we have planning to extend the proposed method to video super-resolution. We are also interested in applying the gradient profile prior to other image reconstruction applications.

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