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Super Resolution and Image Enhancement in Remote Sensing Area.

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Abstract

Image processing is a physical process used to convert the image signal into a physical image (the single may be either analog or digital). Super-Resolution is a method in the remote sensing area where mixed pixel is divided into sub pixel and for which every sub pixel will be classified. Remote sensing is playing an increasingly important role in mapping and monitoring the earth. There are several constraints that make high spatial resolution (HR) remote sensing imagery with a high spectral definition difficult to obtain. We propose a new SR method (HMT theory to set up a prior model) by using the concept of image enhancement, reconstruction, and robust algorithm for providing a super resolution remote sensing image. We worked on satellite images.

1. Introduction [e] [f]

We use the theory to set up a prior model for reconstructing super resolved images from a sequence of LR images. The method proposed in this paper is based on the HMT theory in the wavelet domain. We use the HMT theory to set up a prior model for reconstructing super resolution images from a sequence of wrapped, blurred, sub sample and noise contaminated low resolution images. We also increase the pixel density and cover a large amount of area and destroy the blurs by using deploring and reboot the image to avoid the wrapper, blurred and noise.

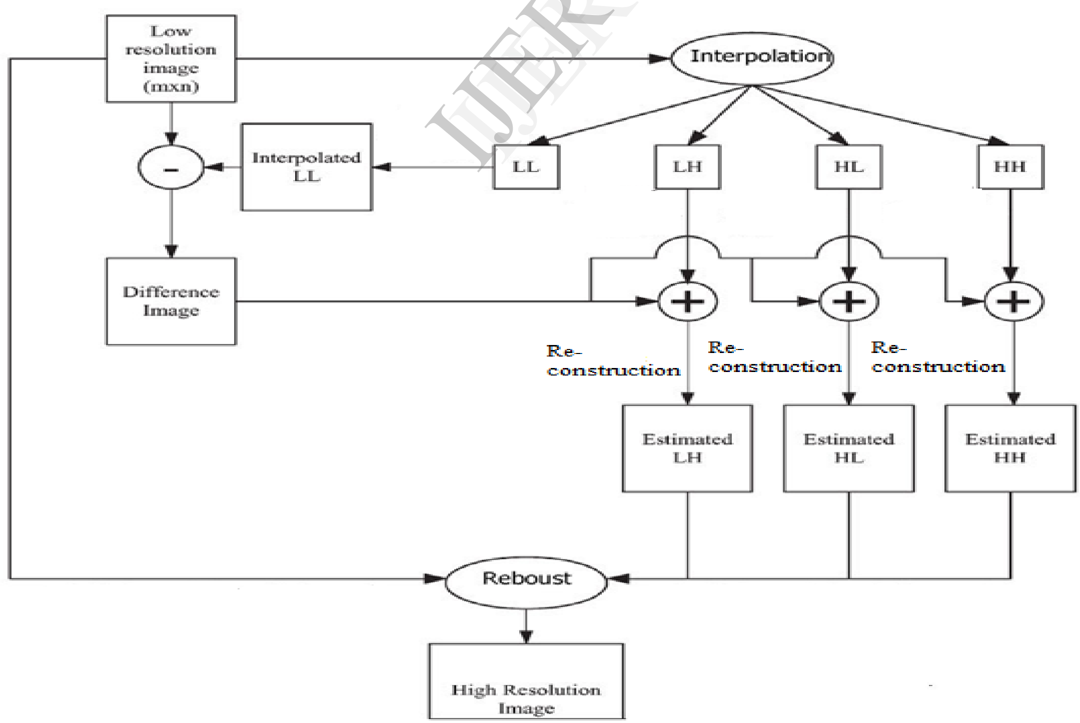

Fig. Overall process

The flow diagram will clearly explain the flow of the process throughout the system. The design phase is essentially the connecting bridge between the user requirement specification and the final solution for satisfying the requirements. The goal of the design phase is to produce a system model or representation that can be used later to build the system.

1.1. Initialization

When you process an image, all the operations and settings you specified in your Image Processor instance are performed on your input image An image is taken as the input. The image is then loaded and then initialization is done. Input image are loaded in the form of (m*n) .

When the image is of low resolution, low frequency matrix differentiation used to resolute a better low resolution image.

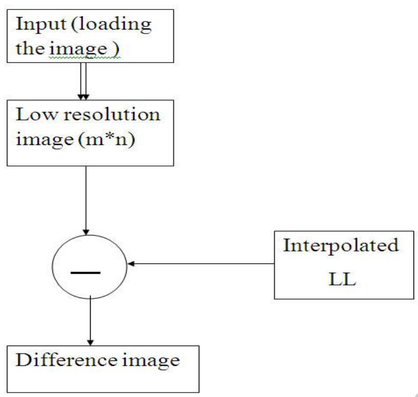

Fig. Initialization module

Initialization of our project is given as follows,

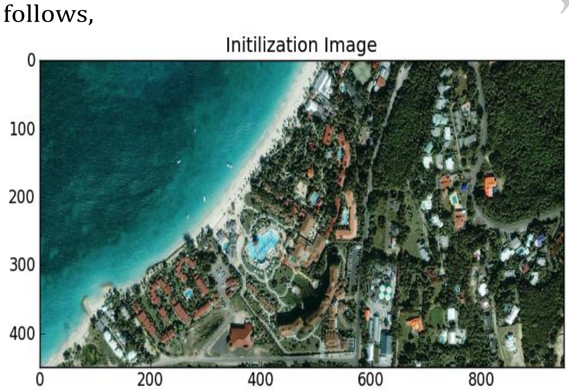

Fig. Initialization image

1.2. Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels are also called as super-pixels). The process of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easy to analyse. Image-segmentation is typically used to locate objects and boundaries (boundaries such as lines, curves, etc.).Image-segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the full image, or a part of the image extracted from the input image. Each pixel in a region is similar with respect to some computed property or characteristic, such as colour, texture, or intensity. Adjacent regions are significantly different with respect to the same characteristics.

Segmentation of out project image is given below,

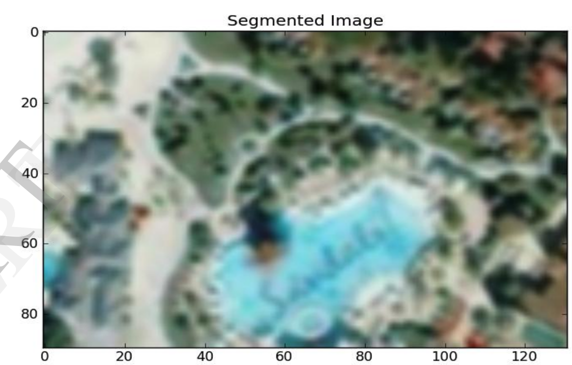

Fig. Segmentation image

1.3. Image Enhancement [c]

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide better' input for other automated techniques of image processing. Techniques Image-Enhancement can be divided into two broad categories:

1. Spatial domain method, operate directly on pixels, and

2. Frequency domain methods, operate on the Fourier transform of an image

Spatial Domain Methods

The value of a pixel with coordinates (x, y) in the enhanced image is the result of performing some operation on the pixels in the diagram.

Neighbourhood of (x, y) in the input image. Let r and s denote any grey level in the original and enhanced image respectively.

If every pixel with level r in original image we create a pixel in the enhanced image with level $S = T(r)$. If $T(r)$ has the form as shown,

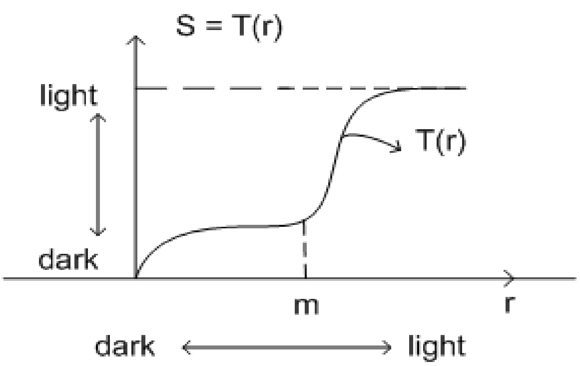

Fig. Spatial Domain Methods

The spatial domain method is used in our project for image enhancement. The result of image enhancement of our input is given below,

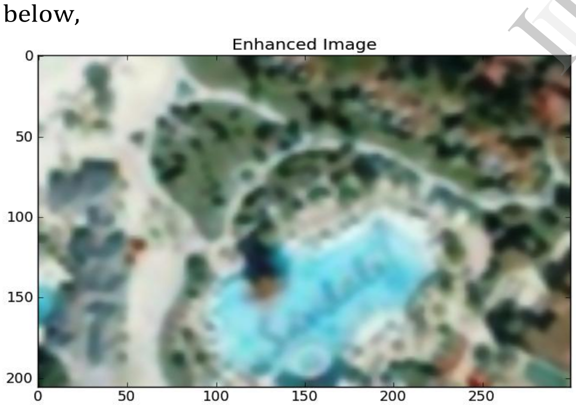

Fig. Enhanced Image

1.4. Reconstruction

Padding the pixel to each frame. If there are enough LR images, we can solve in reality, it is hard to find sufficient numbers of LR images. Use procedure (called regularization) to stabilize the inversion of ill posed problem. Image reconstruction encompasses the entire image formation process and provides a foundation for the subsequent steps of image process.

The goal is to retrieve image information that has been lost in the process of image formation. In the image enhancement, where the appearance of an image is improved to suit some subjective criteria, image reconstruction is an objective approach to recover a degraded image based on mathematical and statistical models.

In a first step, we have to characterize the object of our observations, which could be a faint point source (e.g., A single star in the night-time sky) or a bright extended object such as the Sun. Some of the image degradation is usually attributed to the propagation of the wave or particles. To identify retinal diseases in the posterior of our eye, we have to observe through the turbid vitreous liquid in our eyes and in the case of ground-based astronomical-observations, the Earth's turbulent atmosphere will be degraded and blur images.

Reconstruction of the enhanced image is given below,

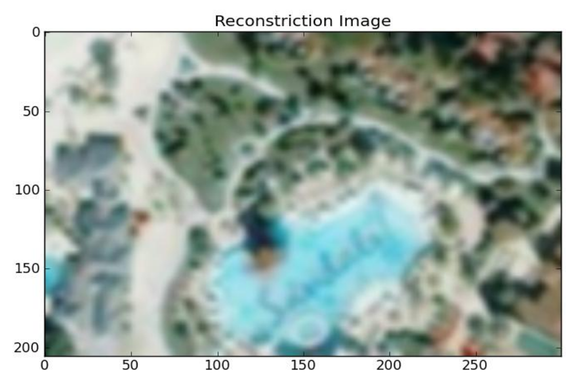

Fig. Reconstruction Image

1.5. Robust [a] [d]

Estimation of an unknown HR image is not exclusively based on the LR measurements. Which is also based on many assumptions, (such as noise or models). These models are not supposed to be exactly true, as they are merely mathematically convenient formulations of some general prior information. From many available estimators, which estimate an HR image from a set of noisy LR images, one may choose an estimation method which

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promises the optimal estimation of the HR frame, based on certain assumptions on data and noise models.

When the fundamental assumptions of data and noise models do not faithfully describe the measured data, the estimator performance degrades. Furthermore, the existence of outliers, which are known as data points with different distributional characteristics than the assumed model, will produce erroneous estimates. A method which promises optimality for a limited class of data and noise models may not be the most effective overall approach. Often, suboptimal estimation methods which are not as sensitive to modelling and data errors may produce better and more stable results (robustness). To study the effect of outliers, the concept of a breakdown point has been used to measure the robustness of an algorithm.

The breakdown point is the smallest percentage of outlier contamination that may force the value of the estimate outside some range . For instance, the breakdown point of the simple mean estimator is zero, meaning that one single outlet is sufficient to move the estimate outside any predicted bound. A robust estimator,

Such as the median estimator, may achieve a breakdown equal to 0.5, which is the highest value of breakdown points. This suggests that median estimation may not be affected by data sets in which outer contaminated measurements from less that 50% of all data points.

Given x number of input images g1, ... , gn, the image formation process of gk from the super resolved image f can be formulated in the following way[b],

$$\vec{Y}_k = D_k C_k \vec{F}_k \vec{X} + \vec{E}_k$$

where,

$\vec{X}$, high resolution image f reordered in a vector.

$\vec{Y}_k$, k-th input image g_k reordered in a vecror.

$\vec{E}_k$, Normally distributed additive noise re-ordered in a vector.

$\vec{F}_k$, Geometric warp matrix.

C_k, Blurring matrix.

D_k, Decimation matrix.

The total sequared errors of the resampling the high resolution image is,

$$L(\vec{X}) = \frac{1}{2} \sum_{k=1}^{n} \left\| \vec{Y}_k - D_k C_k F_k \vec{X} \right\|_2^2$$

Then substituting derivative of L with respect to $\vec{X}$, the gradient of L define as sum of gradients computed over the input images.

$$\vec{B}_k = F_k^T C_k^T D_k^T (D_k C_k F_k \vec{X} - \vec{Y}_k)$$

$$\nabla L(\vec{X}) = \sum_{k=1}^{n} \vec{B}_k$$

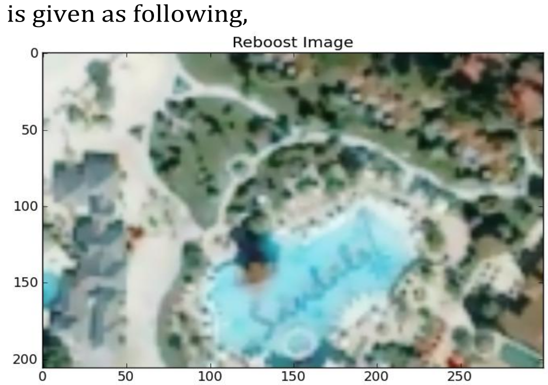
Updating the solution using the simplest gradient based iterative minimization method updates the solution estimate in each iteration by,

$$\vec{X}^{n+1} = \vec{X}^{n} + / \nabla L(\vec{X})$$

To introduce robustness to the procedure, the sum of images in the $\vec{B}_k$,is replaced with a scaled pixelwise medium as shown below,

$$\nabla L\left(\vec{X}\right)(x,y) \approx n.median\left\{ \vec{B}_k (x,y) \right\}_{k=1}^{n}$$

The input and output of the reboustness is given as following,



Conclusion

Our method produces excellent super resolution results both on simulated and real data. Prior model with enlarged reference image in the wavelet domain, the SR optimization method is adapted to provide a clear SR image from multiple LR image by declaring and rebooting.

References

[a] Assaf Zomet, Alex Rav-Acha, Shmuel Peleg, "Robust Super-Resolution", School of Computer Science and Engineering, The Hebrew University of Jerusalem, 91904. Jerusalem, Israel.

[b] M. Elad and A. Feuer. Restoration of a single superresolution image from several blurred, noisy, and undersampled measured image. IP, 6(12): 1646-1658, December 1997.

[c] Capel. D and Zisserman. A. Superresolution enhancement of test image sequence. In Int. Conf. Pattern Recongnition, pages Vol 1: 600-605,2000.

[d] Black. M and Anandan. P The robust estimation of multiple motion: Parametric and piecewise smooth flow fields. CVIU, 63(1): 75-104, january 1996.

[e] A Novel Interpolation Based Super-Resolution of the Cropped scene from a video. A. John, Sakthivel Punniakodhi, Ramesh Murukesan. IJERT : 2012.

[f] E.C.Pasztor, W.T.Freeman and O.T.Carmichael,"learning low level vision"; international journal of computer vision, 2000.