COLORIMETRICALLY RESOLUTION ENHANCEMENT METHOD FOR SATELLITE IMAGERY TO IMPROVE LAND USE

Merugu Suresh[1], Dr Kamal Jain[1]

[1]Department of Civil Engineering, Indian Institute of Technology Roorkee, India. sureshmerugu.iitr@gmail.com.

Abstract:

Satellite images are well used in many scientific applications such as geosciences, astronomy, remote sensing and geographical information systems. One of the most important quality and quantitative factors in images comes from its resolution especially at spatial or spectral. Colorimetry based Interpolation in advance image processing method to increase the resolution of a digital image. In this paper, a resolution enhancement technique for satellite imagery based on Colorimetric with tristimulus variations at subpixel level is used to decompose an input low resolution satellite image into different subbands. Then, the high frequency subband images and the input image are interpolated, followed by combining all these images to generate a new high resolution image by using colorimetry with tristimulus values to monitor the threat, illegal work sites, infrastructural damages (like roads, dams power plants, buildings and embankments) caused by natural disaster and is better to improve land use.

Where the high frequency subbands in six different directions contribute to the sharpness of the high-frequency details such as edges using ArcGIS. The quantitative peak signal to noise ratio (PSNR), root mean square error (RMSE) and visual results show the superiority of the proposed technique over the conventional interpolation methods

About the Author:

MR. Merugu Suresh

Name: **Merugu Suresh**

Date of Birth: 16/08/1979

Designation: Ph. D, Research Scholar

Organization: Indian Institute of Technology Roorkee

Specialization: Digital Image Processing, Remote Sensing and GIS

E mail ID: sureshmerugu.iitr@gmail.com

Contact No: +91 – 8126906333

Key Words: Colorimetry, Image Processing, Resolution, Interpolation, Subpixel Analysis, Remote Sensing & GIS.

1. Introduction

The growing use of Geographic Information Systems (GIS) has led to new research opportunities in the application of satellite imagery to urban analysis. The information content of such images is a function of the combined influence of the radiometric, spatial, and spectral resolution of the sensor. The different bands of satellite sensors are recorded synchronously so that their pixels may be precisely matched and compared with their counterpart pixels in other bands. This means that we can use spectral ("colour") differences to identify urban features to the extent that colours are diagnostic sort of a coarse spectroscopy from space.

Spectral sensor technology, however, coupled with the complexity of ground features in urban areas, can make visual interpretations of satellite imagery both labour intensive and uncertain. Moreover, the informational utility of a multispectral image for land cover classification is often limited by the spectral and spatial resolution of the imaging system. No currently existing single system offers both high spatial and high spectral resolution. Furthermore, if the same techniques that were developed for earlier lower resolution satellite imagery are used on high-resolution imagery (such as maximum likelihood classification), the results can create a negative impact. Lower resolution data are not affected greatly by artefacts, such as shadows, and they also “smooth” out variations across ranges of individual pixels, allowing statistical processing to create effective land cover maps. Individual pixels in higher resolution data can represent individual objects and contiguous pixels in an image can vary dramatically, creating very mixed or “confused” classification results.

1.1. Remote Sensing Imagery

There is a long history of using remote sensing as a data source for urban management information. In 1858, Gaspard Felix Tournachon (later known as "Nadar") took the world's first aerial photographs (of Paris and its surrounding countryside) from a hot air balloon (Lillesand et al., 2000). Since then planners, among others, have come to recognise the value of this "bird's eye view" for discovering the distinctive spatial patterns and forms that characterize urban spaces. There is a richly illustrated literature of cityscapes and urban patterns using aerial photos. However, applications of data obtained from satellite platforms at 300 to 600 miles above the earth have remained limited for urban areas for a variety of reasons, including the low resolution of the images, the complexity of ground features in urban areas, and the technological differences with conventional photography. Until recently, low resolution of satellite images has inhibited their use for urban analysis. Planners are used to seeing roads, buildings, and other small structures in aerial photos, and many urban analyses require mapped data to be at that level of detail, say scales of 1:500 to 1:10.000.

The world's first civilian Earth Resources Technology Satellite (ERTS-1), launched in the early 1970s, produced pictures which were too coarse to show details of the built environment. With pixels 80 meters on one side, the pictures from ERTS-1 (later renamed "Landsat") could not be used to locate houses, streets, or individual plots. However, as space sensor technology improved, pixel sizes decreased. The latest Landsat (7), launched in April 1999, produces images with pixel sizes 15 meters square in the panchromatic (black and white) band, 30 meters square in the six visible and near-infrared bands, and 60 meters square in a single heat-sensitive thermal band. These Landsat data are available in image and digital formats from U.S. government and commercial sources at modest prices.

Satellite imagery technology is very different from conventional photography. Landsat's sensors record wavelengths of reflected light ranging from 0.45 mm to 12.5 mm-the visible, near-infrared, short-wave infrared, and thermal infrared portions of the spectrum. The number of spectral bands in civilian imaging satellites has increased from four in the first Landsats to hundreds in today's hyperspectral satellite sensors. These different bands are recorded synchronously so that their pixels may be precisely matched up and compared with their counterpart pixels in other bands. This means that we can use spectral ("colour") differences to identify urban features to the extent that colours are diagnostic sort of a coarse spectroscopy from space. Spectral sensor technology, however, coupled with the complexity of ground features in urban areas, can make visual interpretations of satellite imagery both labour intensive and uncertain.

2. Significance of High Resolution

The image spatial resolution is firstly limited by the imaging sensors or the imaging acquisition device. Modern image sensor is typically a charge coupled device (CCD) or a complementary metal-oxide-semiconductor (CMOS) active-pixel sensor. These sensors are typically arranged in a two-dimensional array to capture two-dimensional image signals. The sensor size or equivalently the number of sensor elements per unit area in the first place determines the spatial resolution of the image to capture. An imaging system with inadequate detectors will generate low resolution images with blocky effects, due to the aliasing from low spatial sampling frequency. In order to increase the spatial resolution of an imaging system, one straight forward way is to increase the sensor density by reducing the sensor size. However, as the sensor size decreases, the amount of light incident on each sensor also decreases, causing the so called shot noise. Also, the hardware cost of sensor increases with the increase of sensor density or correspondingly image pixel density. Therefore, the hardware limitation on the size of the sensor restricts the spatial resolution of an image that can be captured.

While the image sensors limit the spatial resolution of the image, the image details (high frequency bands) are also limited by the optics, due to lens blurs (associated with the sensor point spread function (PSF)), lens aberration effects, aperture diffractions and optical blurring due to motion. Constructing imaging chips and optical components to capture very high-resolution images is prohibitively expensive and not practical in most real applications, e.g., widely used surveillance cameras and cell phone built-in cameras. Besides the cost, the resolution of a surveillance camera is also limited in the camera speed and hardware storage. In some other scenarios such as satellite imagery, it is difficult to use high resolution sensors due to physical constraints. Another way to address this problem is to accept the image degradations and use signal processing to post process the captured images, to trade off computational cost with the hardware cost. These techniques are specifically referred as High Resolution (HR) reconstruction

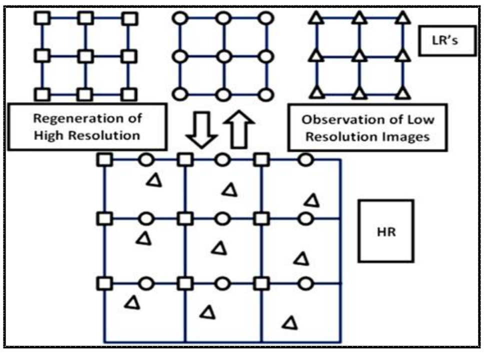

Figure 1: The basic idea for regeneration of High Resolution from multiple low-resolution frames. Subpixel motion provides the complementary information among the low-resolution frames that makes HR Regeneration possible.

3. Proposed Methodology

3.1. Applicability of Image Processing

In this section, applicability of image processing for each proposed method is presented, first. Next, sample processed results are shown. Different liner type damages are collapsed bridge, roads and slope failure on embankment due to natural disaster. For these kinds of damage, end member extraction is good to detect them from images. If damage does not exist, extracted edge is straight. On the contrary, if there is a damage, extracted edge has blurs. The problem to overcome is that not only damage but also shadows are also extracted. In order to remove end member extraction of non damage objects, combination of two image processing; edge extraction and classification, to be tried. Its result is shown in section results and discussions. Some of extracted edge of non damage objects can be removed.

3.2. Colorimetry: CIE Chromaticity Diagram

Colorimetry is the science of measuring, representing, and computing color in a way that takes into account the interaction between the physical aspects of color and the physiological aspects of human vision. The basis of colorimetry is a set of standards defined by Commission Internationale de l Eclariage (CIE), the primary organization for the standardization of colorimetry and terminology. The sensory expression of color is thus dependent on the interaction of three different elements: a light source, an object and an observer. This involves both physical aspects of color, such as the spectral interaction between the light and the object, and physiological aspects of human vision. The interaction between these two aspects, the psychophysical aspect, dealing with the relation between physical attributes and the resulting sensations, is defined by colorimetry (Suresh et al., 2013).

The CIE has defined a system that classifies colour according to the HVS (the human visual system). Using this system we can specify any colour in terms of its CIE co-ordinates and hence be confident that a CIE defined colour will match another with the same CIE definition. The CIE has measured the sensitivities of the three broad bands in the eye by matching spectral colours to specific mixtures of three colored lights. The spectral power distribution (SPD) of a colour is cascaded with these sensitivity functions to produce three tri-stimulus values. These tri-stimulus values uniquely represent a colour, however since the illuminant and lighting and viewing geometry will affect the measurements these are all carefully defined. The three CIE tri-stimulus values are the building blocks from which many colour specifications are made. A colour can be described as a mixture of three other colours or "Tristimuli". Typically RGB for CRT based systems (TV, computer) or XYZ (fundamental measurements). The amounts of each stimulus define the colour.

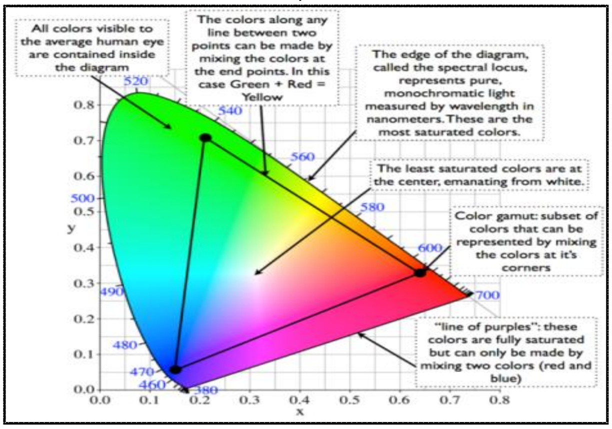

Figure 2: CIE Chromaticity Diagram

However, it is frequently useful to separate the colour definition into "luminance" and "chromaticity". Lower case is always used to signify chromaticity coordinates; upper case always signifies tristimulus values (or amounts of the primaries). Chromaticity coordinates can be plotted on a two-dimensional diagram that defines all the visible colours, luminance is normal to that diagram.

3.3. Iterative Back Projection

Image interpolation using single image basically produce smooth results and loss of high frequency components such as edges. The proposed algorithm regenerates a high resolution image using a set of sub-pixel shifted low resolution images and each sub-pixel displaced stimulus variations in colorimetry contains different information after combining each low resolution image and the high resolution image provides more details than any of the interpolated single image. The ever demanding need for high-resolution imagery stimulated research and development of resolution techniques. The process of taking a sequence of under sampled low resolution images of a particular scene and generating its high quality high resolution image is known as image reconstruction. Due to the relative motion between the camera sensor and scene, each low resolution frame acquired, contains slightly different information about the scene. High resolution takes advantage of this distinct information contained in each under sampled low resolution image and fuses the information from all the low resolution frames during the reconstruction process to generate a high quality high resolution image of the true scene.

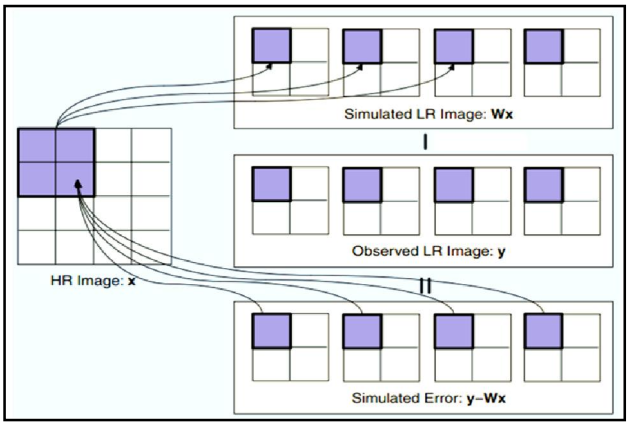

Figure 3: Schematic Diagram of High Resolution Algorithm. A High Resolution reconstructed image, which gives simulated low resolution images that are as close as possible to the observed low resolution images.

The above shown algorithm is for solving the high resolution problem is iterative. Starting with initial guess $f^{(0)}$ for the high resolution image, the imaging process is simulated to obtain a set of low resolution images $\{g_k^{(0)}\}$ corresponding to the observed input images $\{g_k\}$. If $f^{(0)}$ were the correct high resolution image, then the simulated images $\{g_k^{(0)}\}$ should be identical to the observed images $\{g_k\}$. The difference images $\{g_k - g_k^{(0)}\}$ are then computed, and used to improve the initial guess by back projecting each value in the difference images onto its respective field in $f^{(0)}$. This process is repeated iteratively to minimize the error function.

$$e^{(n)} = \sqrt{\sum_k \sum_{(x,y)} (g_k(x, y) - g_k^{(n)}(x, y))^2} \quad (1)$$

Definition 1: A low resolution pixel **y** is influenced by a high resolution pixel **x**, if **x** is in **y**'s respective field.
Definition 2: A low resolution image **g** is influenced by a high resolution pixel **x**, if **g** contains a pixel **y** such that **y** is influenced by **x**.
The following notation is used: f, the target high resolution image to be constructed (unknown). $f^{(n)}$, the approximation of f obtained after n iterations. g_k, the kth observed low resolution image. $g_k^{(n)}$, the low resolution image obtained by applying in simulated imaging process to $f^{(n)}$, if $f^{(n)}$is the correct high resolution, we expect $g_k^{(n)} = g_k$. h^{PSF}, the point spread function of the imaging blur. h^{BP}, a back projection kernel. **x** denotes a high resolution pixel. **y** denotes a low resolution pixel (influenced by **x**). Let $\mathbf{z_y}$ denotes the center of the receptive field of **y** in $f^{(n)}$. The imaging process is then expressed by

$$g^{(n)}(\mathbf{y}) = \sum_{\mathbf{x}} f^{(n)}(\mathbf{x}) h^{\mathrm{PSF}}(\mathbf{x} - \mathbf{z_y}) \quad \ldots (2) \qquad f^{(n+1)}(\mathbf{x}) = f^{(n)}(\mathbf{x}) + \sum_{\mathbf{y} \in \cup_k Y_{k,\mathbf{x}}} (g_k(\mathbf{y}) - g_k^{(n)}(\mathbf{y})) \frac{(h_{\mathbf{xy}}^{\mathrm{BP}})^2}{c \sum_{\mathbf{y}' \in \cup_k Y_{k,\mathbf{x}}} h_{\mathbf{xy}'}^{\mathrm{BP}}} \quad \ldots (3)$$

The iterative update scheme to estimate the high resolution image f is expressed by $Y_{k,x}$ denotes the set $\{\mathbf{y} \in g_k \mid \mathbf{y}$ is influenced by x$\}$, c is a (constant) normalizing factor, $h_{xy}^{BP} = h^{BP}(x - \mathbf{z_y})$.
In the above equation the value of $f^{(n)}$ at each high resolution pixel x is updated according to all low resolution pixels y which it influences. The contribution of the low resolution pixel y of an input image g_k is the error (g_k (**y**) - ($g_k^{(n)}$ (**y**)) multiplied by a factor of h_{xy}^{BP}/c. Therefore strongly influenced low resolution pixels also strongly influence $f^{(n+1)}$ (**x**), while weakly influenced low resolution pixels hardly influence $f^{(n+1)}$ (**x**). Since receptive fields of different low resolution pixels overlap, $f^{(n+1)}$ (**x**)'s new value is influenced by several low resolution pixels. All corrections generated by the various low resolution pixels are combined by taking their weighted average, using the coefficients of h^{BP} as weights.

4. Results and Discussions

In this paper, the proposed method has been tested on several different satellite images. In order to show the superiority of the proposed method over the conventional bicubic interpolation techniques from visual point of view Figures 4 to 6 are included. In these figures with low resolution satellite images, the enhanced images by using the proposed techniques based on image resolution enhancement are shown to get the infrastructural damages information. It is clear that the resultant image, enhanced high resolution by using the proposed technique is much better than the other techniques to improve the land use. Not only visual comparison but also quantitative comparisons are confirming the superiority of the proposed method.

4.1. Method to designate particular facilities in ArcGIS

Digital register data about facilities is under developing for maintenance. For example, Road Bureau, Ministry of Land, Infrastructure and Transport are now developing road GIS data. This data includes polygon of structures like bridge. If you highlight particular facility on the remote sensing images based on the road GIS data, you can focus on the target facility quickly among images of wide area. In result, you can easily and rapidly find whether there is damage on the particular facility (Figure 4). Another method is to use line data instead of polygon data. This is proper to liner-type facilities such as roads and embankments. You can check along the line.

4.2. Method to mask some parts

This is the method to mask parts that you do not need to watch in a remote sensing image. You can easily focus on only what you have to check. Road center is used as base line. The area without 50m from this road center line is masked (white area in Figure 4). Distance of buffering should be adjusted according to what damage is detected. Figure 4(a) & 4(b) is sample image. One can focus on the target facility quickly among images of wide area. In result, you can easily and rapidly find whether there is damage on the particular facility (Figure 5).

4.3. Method to zoom in a target point

This method is not data-overlaying. ArcGIS software has the function to zoom in an object. If you use this function when you read images, it becomes easy to find facility damage/blurs from images. Figure 5 is sample to apply this method. You move your mouse to where you want to check the existence of facility damage. This is also applied after image processing.

Figure 4: (a) Method to designate particular facilities (b) Method to zoom in a target point

Figure 5: (a) Gray Image (b) Edge Extracted Image and Reconstructed High Resolution Image

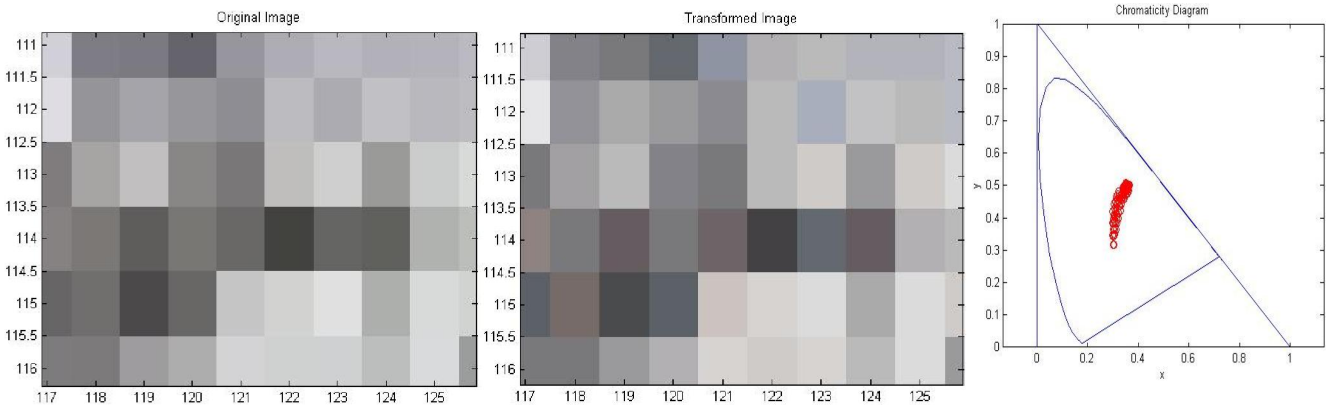

Figure 6: Original and Transformed image using colorimetry based tristimulus variations at subpixel level

It seems difficult to focus on the target facilities from images of wide area. Disadvantage of information extraction by human eyes is that it takes longer time to complete extract facility damage. To improve these situations, we conducted technology development to overlay data related to facility on remote sensing image data to support extraction by human. In this section, some examples are presented below.

In the pre disaster image, pixels whose intensity value is very different from adjacent pixels' are expressed light, and vice versa. By edge extraction, information that has no relation with damage such as shadow cannot remove. In the post disaster image, if the distribution of the intensity value of a pixel and its adjacent ones is large, the pixel is shown as light, and vice versa.

Conclusion:

For aerial-type damage like slope failure, edge extraction, sub pixel analysis with tristimulus variations using x, y values in CIE chromaticity diagram, edge enhancement and operations between images are suitable to detect damaged area. In this way, it is possible to find aerial-type damage. However, for liner-type damage such as horizontal difference, it is comparatively used to detect damages. In this case, extraction by human should be applied and in order to help staff to extract, it is effective to overlay other data to focus on specific area/facility to check.

In this paper, we reconstructed a high resolution image from multi-resolution, low resolution images using colorimetry to detect the infrastructural damages. Low resolution images have been sub sampled and displaced by sub-pixel shifts with respect to tristimulus variations in colorimetry. Colorimetry classifies low resolution satellite images at subpixel level based on stimulus values using CIE chromaticity diagram. Experimental results show that proposed algorithm is good for preserving high frequency components such as edges to get exact defect.

Based on experimental results the performance of the proposed algorithm is visually better compared to other methods. In future by using the tristimulus values and based on density of color variations to restore the exact artifacts in multispectral images for different regions using colorimetry.

References:

1. **Bates P.D, Marks K.J, Horritt M.S, 2003**. Optimal use of high resolution topographic data in flood inundation models. Hydrol. Process 17, 537–557.
2. **De Moel H, van Alphen J, Aerts J.C.J.H., 2009**. Flood maps in Europe – methods, availability and use. Nat. Hazards Earth Syst. Sci. 9, 289–301.

3. **Dodov B, Foufoula Georgiou E., 2005**. Floodplain morphometry extraction from a high resolution digital elevation model: a simple algorithm for regional analysis studies. Res. Rep. Ser. Univ. of Minn. http:// static.msi.umn.edu/reports/2005/1.pdf
4. **Huang T. S, Tsai Y R., 1984**. Multi frame image restoration and registration. Adv Computer Vision Image Process 1: 317–339.
5. **Hung K.W, and Siu W. C., 2012**. "Single image super-resolution using iterative wiener filter," in Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE Int. Conference on. pp. 1269–1272.
6. **Kumar C, Ananthashayana V., 2009.** "Super resolution reconstruction of compressed low resolution images using wavelet lifting schemes," in Computer and Electrical Engineering, Second Int. Conf., vol. 2. IEEE, pp. 629–633.
7. **Lillesand T.M and Kiefer R.W., 2000,** Remote Sensing and Image Interpretation, 4th edition, New York, Wiley & Sons.
8. **Parulski K.A, D' Luna L.J, Benamati B.L, Shelley P.R., 1992.** High performance digital color video camera. J Electron Imaging 1:35–45.
9. **Piao Y, Shin I, and Park H. W., 2007.** "Image resolution enhancement using inter subband correlation in wavelet domain," in Proc. Int. Conf. Image Process., San Antonio, TX, pp. I-445–I-448.
10. **Suresh Merugu, Kamal Jain., 2013**. "Sub Pixel Analysis on Hypothetical Image by using Colorimetry" International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume 2, Issue-4, September 2013.
11. **Sanada A., 2004.** Draft Manual for the application of remote sensing technologies to detect facilities damage, Technical note of National Institute for land and infrastructure management, Japan.
12. **Storkey A. J., 2003**. "Dynamic structure super-resolution," Advances in Neural Information Processing Systems, pp. 1319–1326.
13. **Tekalp A. M, Ozkan M. K and Sezan M. I., 1992**. "High-resolution image reconstruction from lower-resolution image sequences and space-varying image restoration," in Acoustics, Speech, and Signal Proc., IEEE Int. Conference, vol. 3. pp. 169–172.
14. **Vandewalle P, Siu S, Vetterli M., 2006.** "A frequency domain approach to registration of aliased images with application to super-resolution," EURASIP Journal on Advances in Signal Proc., vol.1
15. **Xiong Z, Sun X, and Wu F., 2010.** "Robust web image/video superresolution," Image Processing, IEEE Transactions on, vol. 19, no. 8, pp. 2017–2028.