

Image Processing With Sampling and Noise Filtration in Image Reconigation Process

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Abstract: Contrast enhancement is a very critical issue of image processing, pattern recognition and computer vision. This paper surveys image contrast enhancement using a literature review of articles from 1999 to 2013 with the keywords Image alignment theory and fuzzy rule-based and explore an idea how set theory image processing rule-based improve the contrast enhancement technique in different areas during this period. Image enhancement improves the visual representation of an image and enhances its interpretability by either a human or a machine. The contrast of an image is a very important attribute which judge the quality of image. Low contrast images generally occur in poor or nonuniform lighting environment and sometimes due to the non-linearity or small dynamic range of the imaging system. Therefore, vagueness is introduced in the acquired image. This vagueness in an image appears in the form of uncertain boundaries and color values. Fuzzy sets (Zadeh, 1973) present a problem solving tool between the accuracy of classical mathematics and the inherent imprecision of the real world.

Keywords: Image alignment, extrinsic method, intrinsic method, Threshold Optimization, Spatial Filter.

I. Introduction

A monochromatic image is a two dimensional function, represented as $f(x,y)$, where x and y are the spatial coordinates and the amplitude of f at any pair of coordinates (x,y) is called the intensity of the image at that point. When x,y and the amplitude value of f are all finite, discrete quantities, then the image is called a digital image. This function should be non-zero and finite, $0 < f(x,y) < \infty$. Any visual scene can be represented by a continuous function (in two dimensions) of some analogue quantity. This is typically the reflectance function of the scene: the light reflected at each visible point in the scene. The function $f(x,y)$ is a multiplication of two components-

- The amount of source illumination incident on the scene $i(x,y)$
- The amount of illumination reflected by the objects in the scene $r(x,y)$

$f(x,y) = i(x,y) * r(x,y)$ where $0 < i(x,y) < \infty$ and $0 < r(x,y) < 1$.

The equation $0 < r(x,y) < 1$ indicates that reflectance is bounded by 0 (total absorption) and 1 (total reflectance).

Image then $\ell = f(x_a, y_b)$, where ℓ lies in the range $L_{\min} \leq \ell \leq L_{\max}$, L_{\min} is positive and L_{\max} is finite. In general case, ℓ lies in the interval $[0, L-1]$. $\ell=0$ represents black and $\ell=L-1$ represents white. That's why it can be said that ℓ lies in the range black to white. Images can be represented as 2D array of $M \times N$ like that

$$f(x,y) = \begin{bmatrix} f(1,1) & f(1,2) & \dots & f(1,N) \\ f(2,1) & f(2,2) & \dots & f(2,N) \\ \dots & \dots & \dots & \dots \\ f(M,1) & f(M,2) & \dots & f(M,N) \end{bmatrix}$$

Digital images also represent the reflectance function of the scene in the form of sampling and quantizing. They are typically generated with some form of optical imaging device (e.g. a camera) which produces the analogue image (e.g. the analogue video signal) and an analog to digital converter: this is often referred to as a 'digitizer', a 'frame-store' or 'frame-grabber'. Noise is the error which is caused in the image acquisition process, effects on image pixel and results an output distorted image. Noise reduction is the process of removing noise from the signal. Sensor device capture images and undergoes filtering by different smoothing filters and gives processed resultant image. All recording device may suspect to noise. The main fundamental problem is to reduce the noises from the color images. There may introduce noise in the image pixel mainly for three types, such as- i) Impulsive Noise ii) Additive Noise (Gaussian Noise) iii) Multiplicative Noise (Speckle Noise). In impulsive noise, some portion of the image pixel may be corrupted by some other values and the rest

pixels leaves remain unchanged. There are two types of Impulsive noise- a) Fixed values Impulse noise b) Randomly valued impulse noise. When value from a certain distribution is added to the image pixel, then additive noise occurs. Example Gaussian Noise. Multiplicative noise is generally more difficult to remove from the images than additive noise because the intensity of the noise varies from the signal intensity (e.g. Speckle Noise).

II. Image sampling

1. SAMPLING:

Sampling is the process of examining the value of a continuous function at regular intervals. Suppose we take an example $y = \sin(x) + \frac{1}{3}\sin(3x)$ and sample it at ten evenly spaced value of x which can be graphically plotted as shown in the picture, though it is *under sampling* where the numbers of the samples are not sufficient to reconstruct the signal. Suppose we sample the function at 100 points, then we can clearly reconstruct the functions and all its properties can be determined from the sampling.



Figure 1.1: Sampling a function- Under Sampling

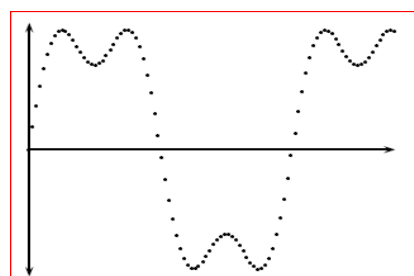


Figure 1.2: Sampling a function with More Points

We might measure the voltage of an analog waveform every millisecond, or measure the brightness of a photograph every millimeter, horizontally and vertically. We have enough sample points but the main requirement is that the Sampling Period is not greater than one half the finest detail in our function. This is known as “Nyquist Criterion” which can be stated as the Sampling Theorem which says that “A continuous function can be reconstructed from its samples provided that the sampling frequency is at least twice the maximum frequency in the function.” Sampling rate is the rate at which we make the measurements and can be defined as **Sampling Rate=1/Sampling IntervalHz** If sampling is performed in the time domain, Hz is cycles/sec. If one sample I taken over T seconds and the sampling frequency represented as $f_s = 1/T$ Hz. The sampling frequency can also be stated in terms of radian, denoted by $\omega_s = 2\pi f_s = 2\pi/T$. In the case of image processing, we can regard an image as a two-dimensional light intensity function $f(x; y)$ of spatial coordinates $(x; y)$. Since light is a form of energy, $f(x; y)$ must be nonnegative. In order that we can store an image in a computer, which processes data in discrete form, the image function $f(x; y)$ must be digitized both spatially and in amplitude. Digitization of the spatial coordinates $(x; y)$ is referred to as image sampling or spatial sampling, and digitization of the amplitude f is referred to as quantization. Sometimes some averaging or integration over a small interval occurs so that the sample actually represents the average value of the analog signal in some interval. For example, if the original signal $x(t)$ is changing particularly rapidly compared to the sampling frequency or is particularly noisy, then obtaining samples of some averaged signal can actually provide a more useful signal with less variability. This is often modeled as a convolution- namely, we get samples of $y(t)=x(t)*h(t)$, where $h(t)$ represents the impulse response of the sensor or digitizer.

2. SAMPLING THEOREM:

In this section we discuss the Sampling Theorem, also called the Shannon Sampling Theorem or the Shannon-Whitaker-Kotelnikov Sampling Theorem, after the researchers who discovered the result. This result gives conditions under which a signal can be *exactly* reconstructed from its samples. The basic idea is that a signal that changes rapidly will need to be sampled much faster than a signal that changes slowly. It is a beautiful example of the power of frequency domain ideas. Consider a sinusoid $x(t) = \sin(\omega t)$ where the frequency ω is not too large. In the ideal sampling one sample takes T seconds. Then the sampling frequency in Hertz is given by $f_s = 1/T$ and in radians by $\omega_s = 2\pi/T$. If we sample at rate fast compared to ω , that is if $\omega_s \gg \omega$ then we can easily conclude that we have a sinusoid with ω not too large, it seems clear that we can exactly reconstruct $x(t)$. On the other hand, if the number of samples is small with respect to the frequency of the sinusoid then we are in a situation such as that depicted in Figure. In this case it is difficult to reconstruct $x(t)$, but the samples actually appear to fall on a sinusoid with a lower frequency than the original. Thus, from the samples we would probably reconstruct the lower frequency sinusoid. This phenomenon is called *aliasing*, since one frequency appears to be a different frequency if the sampling rate is too low. It turns out that if the original

signal has frequency f , then we will be able to exactly reconstruct the sinusoid if the sampling frequency satisfies $f_s > 2f$, that is, if we sample at a rate faster than twice the frequency of the sinusoid. If we sample slower than this rate then we will get aliasing, where the alias frequency is given by $f_a = |f_s - f|$.

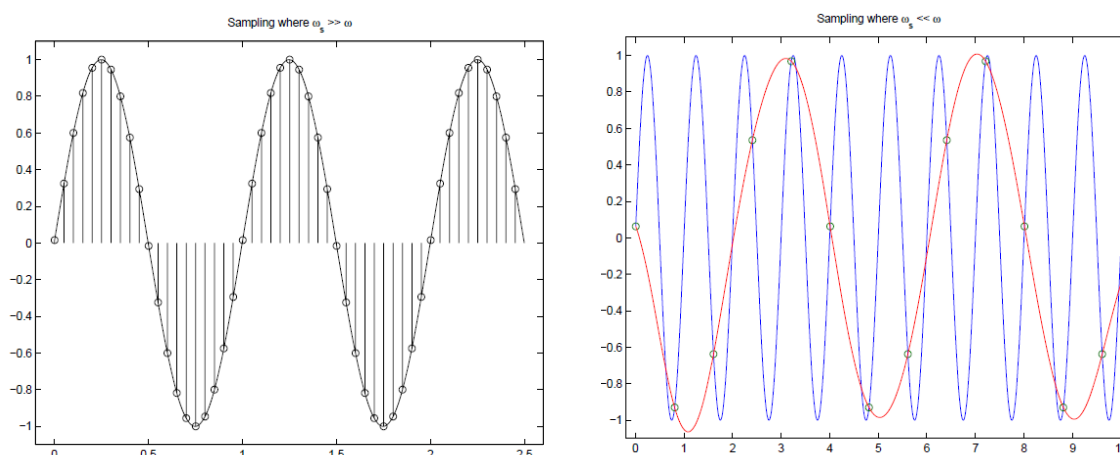


Fig:
-1.3

3. METHODS OF SAMPLING:

Method of Sampling determined by the sensor arrangement:

- Single sensing element combined with motion: spatial sampling based on number of individual mechanical increments.
- Sensing strip: the number of sensors in the strip establishes the sampling limitations in one image direction; in the other: same value taken in practice
- Sensing Array: the number of sensors in the array establishes the limits of sampling in both directions.

We can explain the procedure of converting the continuous signal into the Digital form using Sampling and Quantization by the help of some pictures:

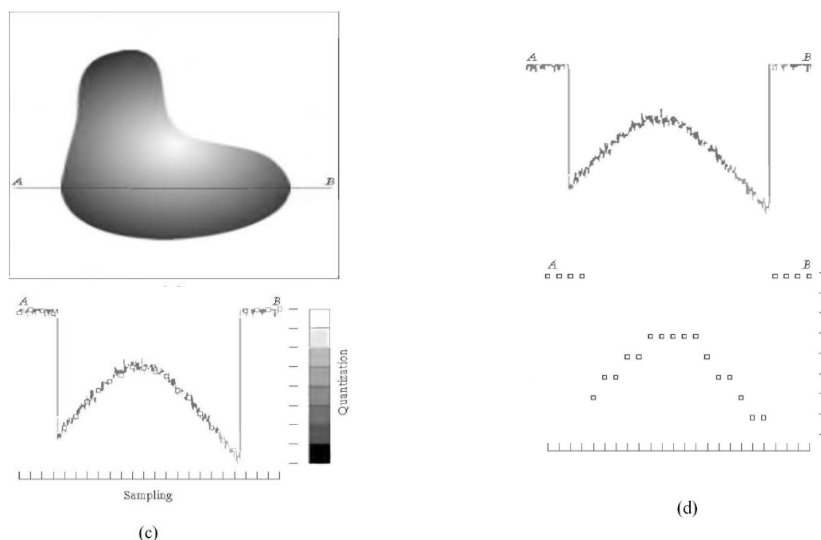


Fig 2: Generating digital Image, a)Continuous Image, b) A Scan line from A to B in the continuous image, c) Sampling and Quantization, d) Digital Scan Line

At first we plot the amplitude values (gray level) of the continuous image along the line segment AB. To sample this function, we take equally spaced samples along the line AB. The samples are shown a small white square superimposed on the function. The set of these discrete locations gives the sampled function. In order to form a digital function, the gray-level values also must be converted (quantized) into discrete quantities. The right side of Figure 2(c) shows the gray level scale divided into eight discrete levels, ranging from black to

white. The continuous gray levels are quantized simply by assigning one of the eight discrete gray levels to each samples. The digital samples resulting from both sampling and quantization are shown in the Figure 2(d). Starting at the top of the image and carrying out this procedure line by line produces a two dimensional digital image.

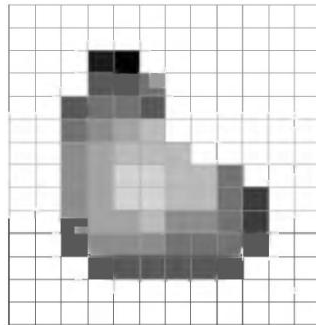


Fig 3:Digital Images Resulting From Sampling and Quantization

Moreover, for moving video images, we have to digitize the time component and this is called temporal sampling.

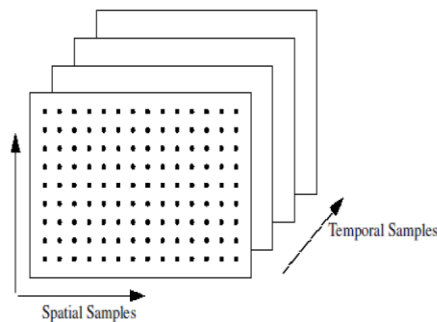


Fig.2.1

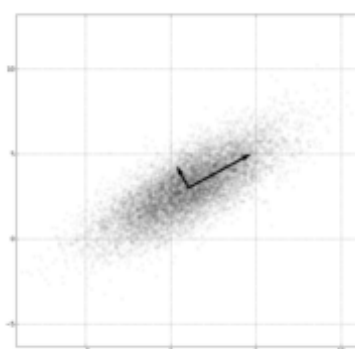
4. SPATIAL SAMPLING:

Usually, a two-dimensional (2D) sampled image is obtained by projecting a video scene onto a 2D sensor, such as an array of Charge Coupled Devices (CCD array) . For colour images, each colour component is filtered and projected onto an independent 2D CCD array. The CCD array outputs analogue signals representing the intensity levels of the colour component. Sampling the signal at an instance in time produces a sampled image or frame that has specified values at a set of spatial sampling points in the form of an N X M array as shown in the following equation.

III. Image Processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of Multidimensional Systems. Digital image processing allows the use of much more complex algorithms for image processing, and hence, can offer both more sophisticated performance at simple tasks, and the implementation of methods which would be impossible by analog means. In particular, digital image processing is the only practical technology for: 1) Classification, 2) Feature extraction, 3) Pattern recognition, 4) Projection and 5) Multi-scale signal analysis. Some techniques which are used in digital image processing include: a) Pixelization, b) Linear filtering, c) Principal components analysis, d) Independent component analysis, e) Hidden Markov models, f) Partial differential equations, g) Self-organizing maps, h) Neural networks, i) Wavelets. Digital Image Processing can be applied in different areas like: 1) Digital Camera Images, 2) Photography, 3) Medical Diagnosis and 4) Intelligent Transportation System etc. Our project will work with pixelization technique. The Theoretical background of the term is described on the following section.

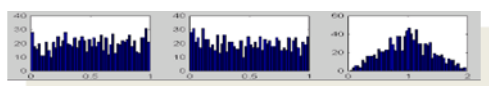
IV. Pixelization



PCA of a multivariate Gaussian distribution

VII. Independent component analysis

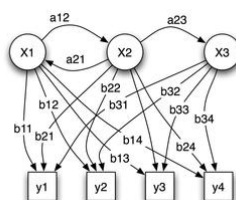
Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals. It is a special case of blind source separation. It is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals.



ICA Principal (Non-Gaussian is Independent)

VIII. Hidden Markov model

A hidden Markov model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (*hidden*) states.



Probabilistic parameters of a hidden Markov model

IX. Partial differential equation

Partial differential equations (PDE) are a type of differential equation, i.e., a relation involving an unknown function (or functions) of several independent variables and their partial derivatives with respect to those variables. A partial differential equation (PDE) for the function $u(x_1, \dots, x_n)$ is of the form

$$F(x_1, \dots, x_n, u, \frac{\partial}{\partial x_1}u, \dots, \frac{\partial}{\partial x_n}u, \frac{\partial^2}{\partial x_1 \partial x_1}u, \frac{\partial^2}{\partial x_1 \partial x_2}u, \dots) = 0$$

X. Wavelet

A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal.

1. DIGITAL IMAGES:

The images are displayed as an array of discrete picture elements (pixels) in two dimensions (2D) and are referred to as digital images. Each pixel in a digital image has an intensity value and a location address. The advantage of a digital image compared to the analogue one is that data from a digital image are available for further computer processing. Each pixel can take 2^k different values, where k is the bit depth of the image. If 8

bit image then each pixel can have 256 (2^8) different grey-scale levels. Nuclear medicine images are frequently represented as 8 bits /16bits images. There are different types of images. (i) Binary image (ii) Grey-scale image/intensity image (iii) True colour /RGB(iv) Indexed images. In the nuclear medicine image processing, the grey-scale image is most used. The RGB/true colour image is used when coloring depiction is necessary. The indexed images should be converted to any of the two other types in order to be processed. A true color composite an image data used in red , green and blue spectral region must be assigned bits of red , green ,blue image processor frame buffer memory. In MatLab (Matrix Laboratory) the functions used for image type conversion are : `rgb2gray`, `ind2rgb`, `ind2gray` and reversely. Any image can be also transformed to binary one using the command : `im2bw`. MatLab image tool is a simple and user- friendly toolkit which can use for quick image processing and analysis without writing a code. Digital Image Processing Techniques In satellite image processing : Digital image processings of satellite data can be grouped into three categories : Image Rectification and Restoration, Enhancement and Information extraction. A digital remotely sensed image is composed of picture elements (pixels) located at the intersection of each row i and column j in each K bands of imagery. Each pixel is a number known as Digital Number (DN) or Brightness Value (BV). A process by which an image is geometrically correcting is called Rectification. So, it is the process by which geometry of an image is made planimetric. Rectification is not necessary if there is no distortion in the image. For example, if an image file is produced by scanning or digitizing a paper map that is in the desired projection system. Then that image is already planar and does not require rectification. Scanning and digitizing produce images that are planar. But it do not contain any map coordinate information. These images need only to be geo-referenced, which is a much simpler process than rectification. Ground Control Points (GCP) are the specific pixels in the input image. For which the output map coordinates are known. To solve the transformation equations a least squares solution may be found that minimises the sum of the squares of the errors. when selecting ground control points as their number, quality and distribution affect the result of the rectification. The mapping transformation has been determined a procedure called resampling . Resampling matches the coordinates of image pixels to their real world coordinates . And then writes a new image on a pixel by pixel basis. Since the grid of pixels in the source image rarely matches the grid for the reference image. Using resampling method the output grid pixel values are calculated.

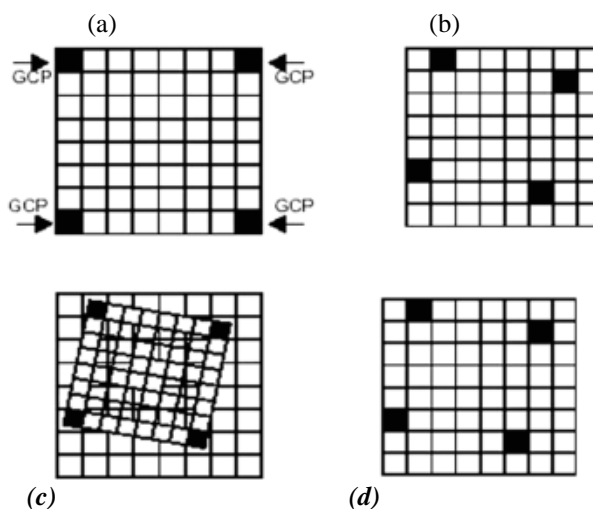


Fig3: Image Rectification (a & b) Input and reference image with GCP locations, (c) using polynomial equations the grids are fitted together, (d) using resampling method the output grid pixel values are assigned (source modified from ERDAS Field guide)

Image enhancement technique is defined as a process of an image processing such that the result is much more suitable than the original image for a 'specific' application. These techniques are most useful for many satellite images .A colour display give inadequate information for image interpretation. There exists a wide variety of techniques for improving image quality. The contrast stretch, density slicing, edge enhancement, and spatial filtering are the more commonly used techniques. Image enhancement is used after the image is corrected for geometric and radiometric distortions. Image enhancement methods are applied separately to each band of a multispectral image. Contrast enhancement techniques expand the range of brightness values in an image. So that the image can be efficiently displayed in a desired manner by the analyst. Linear contrast stretch operation can be represented graphically as shown in Fig. 3. The general form of the non-linear contrast enhancement is defined by $y = f(x)$(1), where x is the input data value and y is the output data value. The non-linear contrast enhancement techniques is useful for enhancing the colour contrast between the nearly

classes and subclasses of a main class. Non linear contrast stretch involves scaling the input data logarithmically. Histogram equalization is another non-linear contrast enhancement technique.

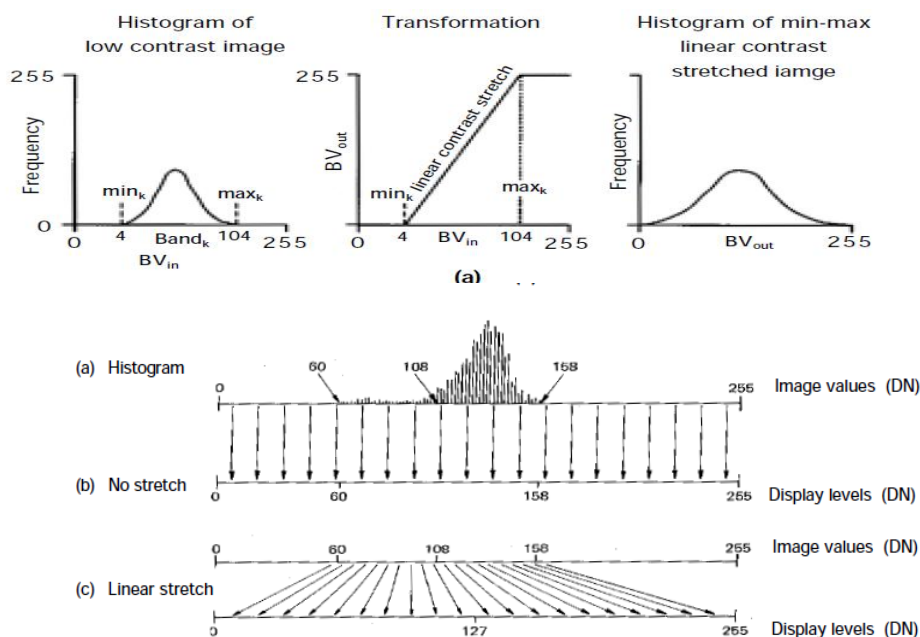


Fig4(a & b): Linear Contrast Stretch (source Lillesand and Kiefer, 1993)

The three types of spatial filters used in remote sensor data processing are : Low pass filters, Band pass filters and High pass filters. The simple smoothing operation will blur the image, especially at the edges of objects. Blurring becomes more severe when the size of the kernel increases. Techniques that can be applied to deal with this problem include (i) by repeating the original border pixel brightness values ,artificially extending the original image beyond its border (ii) based on the image behaviour within a view pixels of the border, replicating the averaged brightness values near the borders. The most commonly used low pass filters are mean, median and mode filters. High-pass filtering is applied to remove the slowly varying components .And it enhance the high-frequency local variations.The high frequency filtered image will have a relatively narrow intensity histogram.The most valuable information that may be derived from an image is contained in the edges surrounding.The eyes see as pictorial edges are simply sharp changes in brightness value between two adjacent pixels.The edges may be enhanced using either linear or nonlinear edge enhancement techniques. In remotely sensed imagery ,a straight forward method of extracting edges is the application of a directional first-difference algorithm and approximates the first derivative between two adjacent pixels.Sometimes differences in brightness values from identical surface materials are caused by shadows, or seasonal changes in sunlight illumination angle and intensity.These conditions may hamper interpreter or classification algorithm to identify correctly surface materials or land use in a remotely sensed image. The mathematical expression of the ratio function is $BV_{i,j,r} = BV_{i,j,k} / BV_{i,j,l}$ (2), where $BV_{i,j,r}$ is the output ratio value for the pixel at row, i, column j; $BV_{i,j,k}$ is the brightness value at the same location in band k, and $BV_{i,j,l}$ is the brightness value in band l. Unfortunately, the computation is not always simple since $BV_{i,j} = 0$ is possible. However, there are alternatives. For example, the mathematical domain of the function is 1/255 to 255 (i.e., the range of the ratio function includes all values beginning at 1/255, passing through 0 and ending at 255). The way to overcome this problem is simply to give any $BV_{i,j}$ with a value of 0 the value of 1. Ratio images can be meaningfully interpreted because they can be directly related to the spectral properties of materials .Fig. 4(a & b) shows a situation where Deciduous and Coniferous Vegetation crops out on both the sunlit and shadowed sides of a ridge.sunlight

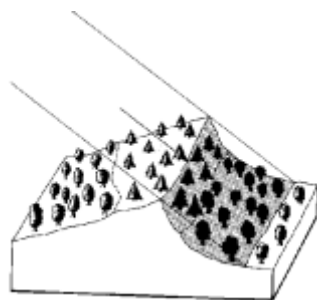


Fig5: Reduction of Scene Illumination effect through spectral ratioing (source Lillesand & Kiefer, 1993)

Landcover/ Illumination	Band A (Digital Number)	Band B (Digital Number)	Ratio
Deciduous			
Sunlit	48	50	.96
Shadow	18	19	.95
Coniferous			
Sunlit	31	45	.69
Shadow	11	16	.69

Most of sensors operate in two modes: multispectral mode and the panchromatic mode. The panchromatic mode corresponds to the observation over a broad spectral band (similar to a typical black and white photograph) and the multispectral (color) mode corresponds to the observation in a number of relatively narrower bands. For example in the IRS – 1D, LISS III operates in the multispectral mode. Multispectral mode has a better spectral resolution than the panchromatic mode. Now coming to the spatial resolution, most of the satellites are such that the panchromatic mode has a better spatial resolution than the multispectral mode, for e.g. in IRS -1C, PAN has a spatial resolution of 5.8 m whereas in the case of LISS it is 23.5 m. The commonly applied Image Fusion Techniques are i) IHS Transformation ii). PCA iii). Brovey Transform iv). Band Substitution. The traditional methods of classification mainly follow two approaches: unsupervised : there are no specific algorithms. The unsupervised approach is referred to as clustering. A cluster is a collection of similar type of objects(data). The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data. One common form of clustering, called the “K-means” clustering also called as ISODATA (Interaction Self-Organizing Data Analysis Technique). Supervised: this has specific algorithms. The basic steps involved in a typical supervised classification procedure are 1. The training stage 2. Feature selection 3. Selection of appropriate classification algorithm 4. Post classification smoothening 5. Accuracy assessment classification algorithms are the parallelepiped, minimum distance, and maximum likelihood decision rules. Parallelepiped algorithm is a widely used decision rule based on simple Boolean “and/or” logic. The parallelepiped algorithm is a computationally efficient method of classifying remote sensor data. Here requires training data. Minimum distance decision rule is computationally simple and commonly used. Like the parallelepiped algorithm, it also requires training data. It is possible to calculate this minimum distance using Euclidean distance based on the Pythagorean theorem. The maximum likelihood decision rule assigns each pixel having pattern measurements. It assumes that the training data statistics for each class in each band are normally distributed i.e Gaussian. Training data with bi-or trimodal histograms in a single band are not ideal. The Bayes’s decision rule is identical to the maximum likelihood decision rule that it does not assume that each class has equal probabilities. The maximum likelihood and Bayes’s classification require many more computations per pixel than either the parallelepiped or minimum-distance classification algorithms. Digital Image Processing Techniques In Identify defect in Plastic (gears) : Digital image processing is a tool to detect the defects of plastic gears on the principle of total quality management. Total quality management aims to hold all parties involved in the production process as accountable for the overall quality of the final product. There are various types of defects that can be present in the plastic gears that can be detected by using image processing are:- 1. Flash: This defect refers to the excess molding material like slide push-out faces, and inserts, etc. in a molten state. 2. Warping: It describes the deformation that occurs when there are differences in the degree of shrinkage at different locations within the molded component. 3. Bubbles: This defect is an air bubble like material trapped inside plastic gear. It occurs during its production. 4. Unfilled sections: When injection molding does not reach certain portions of the inner side of the die before solidifying then this type of defect is occurs. 5. Sink marks: It is the irregular patches on the surface which occur on the outer surfaces of molded components. 6. Ejector marks: Flow marks in which a pattern of the flow tracks of the molten plastic remains on the surface of the molded product. Defect detection starts with image acquisition. The image of the product is obtained by using background illumination which provides excellent contrast nontransparent black object against the illuminated background. Such images are

then segmented by using thresholding. All existing boundaries are traced and for each boundary the pattern vector is calculated. The pattern vectors are compared against the prototype vectors. The results of the algorithms are position of the defects and some of their characteristics, and these are compared with the product prototype. The various stages of development describing algorithms are successfully tested with the limited number of instances and require further testing with greater number of instances. In surface inspection subsystem several algorithms are used which are designed for line detection, spot and blemish detection. The shape inspection subsystem is to detect and classify possible shape defects.



Fig6. Defects that can be identify by using image processing



Fig.7. Defective plastic gears



Fig 8. Non-Defectivplastic gears

Here basically discuss defects develop due to shrinkage, due to overheating and variation in temperature. To identify these kinds of defects, here suggests using SEM (Scanning Electron Microscope) technique. This algorithm is running on the surface as well as the cross-sections of the plastic products. Samples of various internal defects were systematically characterized before and after high temperature processing .A fully robust system taking advantage of image processing techniques (Image segmentation, Non smooth corner detection etc) must be explored to build an economical solution to provide Total Quality Management in manufacturing units .It also allow improvement reducing the cost. There are number of future possibilities for improving the performance of these detection algorithms like usage of machine algorithms(SVM, KNN).

XI. Image Sample Noise Filtration

In this modified spatial filtration approach is suggested for image de noising applications. The existing spatial filtration techniques were improved for the ability to reconstruct noise affected medical images. The modified approach is developed to adaptively decide the masking center for a given MRI image. The conventional filtration techniques using mean, median and spatial median filters were analyzed for the improvement in modified approach. The developed approach is compared with current image smoothing techniques. Digital image processing algorithms are generally sensitive to noise. The final result of an automatic vision system may change according whether the input MRI image is corrupted by noise or not. Noise filters are then very important in the family of preprocessing tools. In appropriate and **coarse** results may strongly deteriorate the relevance and the robustness of a computer vision application. The main challenge in noise removal consists in suppressing the corrupted information while preserving the integrity of fine medical image structures. Several and well-established techniques, such as median filtering are successfully used in gray scale imaging. Median filtering approach is particularly adapted for impulsive noise suppression. It has been shown that median filters present the advantage to remove noise without blurring edges since they are nonlinear operators of the class of rank filters and since their output is one of the original gray values [1][2].

1. SPATIAL FILTRATION:

The simplest of smoothing algorithms is the Mean Filter. Mean filtering is a simple, intuitive and easy to implement method of smoothing medical images, *i.e.* reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in MRI images. The idea of mean filtering is simply to replace each pixel value in an image with the mean ('average') value of its neighbors, including itself. This has the effect of eliminating pixel values, which are unrepresentative of their surroundings. The mean value is defined by,

$$MnF(x_i) = \frac{1}{N} \sum_{i=1}^N x_i \dots\dots\dots(1)$$

Where, N : number of pixels , x_i : corresponding pixel value, $I : 1 \dots N$.

The mean filtration technique is observed to be lower in maintaining edges within the images. To improve this limitation a median filtration technique is developed. The median filter is a non-linear digital filtering technique, often used to remove noise from medical images or other signals. Median filtering is a common step in image processing. It is particularly useful to reduce speckle noise and salt and pepper noise. Its edge preserving nature makes it useful in cases where edge blurring is undesirable. The idea is to calculate the median of neighboring pixels' values. This can be done by repeating these steps for each pixel in the medical image.a) Store the neighboring pixels in an array. The neighboring pixels can be chosen by any kind of shape, for example a box or a cross. The array is called the window, and it should be odd sized.b) Sort the window in numerical order.c) Pick the median from the window as the pixels value.

2. MODIFIED SPATIAL FILTER:

In a Spatial Median Filter the vectors are ranked by some criteria and the top ranking point is used to the replace the center point. No consideration is made to determine if that center point is original data or not.The unfortunate drawback to using these filters is the smoothing that occurs uniformly across the image. Across areas where there is no noise, original medical image data is removed unnecessarily. In the Modified Spatial Median Filter, after the spatial depths between each point within the mask are computed, an attempt is made to use this information to first decide if the mask's center point is an uncorrupted point. If the determination is made that a point is not corrupted, then the point will not be changed.

The proposed modified filtration works as explained below:

- 1) Calculate the spatial depth of every point within the mask selected.
- 2) Sort these spatial depths in descending order.
- 3) The point with the largest spatial depth represents the Spatial Median of the set. In cases where noise is determined to exist, this representative point is used to replace the point currently located under the center of the mask.
- 4) The point with the smallest spatial depth will be considered the least similar point of the set.
- 5) By ranking these spatial depths in the set in descending order, a spatial order statistic of depth levels is created.
- 6) The largest depth measures, which represent the collection of uncorrupted points, are pushed to the front of the ordered set.
- 7) The smallest depth measures, representing points with the largest spatial difference among others in the mask and possibly the most corrupted points, and they are pushed to the end of the list.

XII. Noise Variance Calculation

Estimating the noise standard variance of an image using the wavelet transformation is a good method. After wavelet transformation, image energy mostly locates at the sub bands with large frequency bandwidth, and the high-frequency sub bands with small bandwidth have low energy since their wavelet coefficients are small. Hence, if noise level is very high, the wavelet coefficients of the highest frequency sub band can be regarded as noises and used to estimate the noise variance. An estimation formula of noise variance in wavelet domain given in Ref.[8] is $\sigma = M/0.6745$, where M is the mean value of the amplitudes of wavelet coefficients of HH sub band. The noise estimated by this method may be slightly larger when noise is much lower. Therefore, this method was improved in engineering applications, and two kinds of widely used methods are given as follows. (1) Global variance [9] In this method, all the standard variances used for threshold computation are the same at every decomposition layer and all high-frequency sub bands of every decomposition layer. By using the multi-layer 2D wavelet transformation to a noise image and computing all high-frequency wavelet coefficients, the variance σ can be computed using $\sigma = M1/0.6745$, where $M1$ is the mean value of the amplitudes of wavelet coefficients of all high-frequency sub bands. This method has a good processing effect, but its computational speed is slow.(2) Local variance [10]The characteristic of this method is computing the noise variance of every high-frequency sub band at every wavelet decomposition layer respectively according to the feature that the noises embodied at all high-frequency sub bands of every wavelet decomposition layer are different. The noise variance σ can be computed using $\sigma = M2/0.6745$, where $M2$ is the mean value of the amplitudes of wavelet coefficients of all high-frequency sub bands at every wavelet decomposition layer. The processing effect of this method is inferior to that of the global variance, but its computational speed is faster. Some improvements in local variance estimation method were made in Ref.[10]. Suppose the noise variance of an image $g(i,j)$ is σ_n . Applying the multi-layer orthogonal wavelet transform to image $g(i, j)$, a group of coefficients of wavelet decomposition $Wg(s, j)$ will be generated, $Wg(1, j)\{LHj\}$, $Wg(2, j)\{HLj\}$.

XIII. Threshold Optimization

The smallest change rate of gray level in those regions with significant changes is expressed by threshold t and obtained by IGAE. The concrete algorithm steps are described as follows.

Step 1: Produce the initial antibody population randomly from the solution space.

Step 2: Calculate the object function of each antibody. The gradient vector of binary function $f(x, y)$ can represent the change rate of gray level for an image as well as the direction in which the greatest change occurs. The image gray gradient of pixel $I(x, y)$ at point (x, y) .

Step 3: Compute the individual fitness and save the elitist antibody with the largest fitness into a specified variable. Generally, the fitness function is converted from the object function. It is a minimum problem from the above, so the reciprocal of the object function is used as the fitness function.

Step 4: If the population is of the first generation, go to step 7; otherwise, continue.

Step 5: Compute the fitness of each antibody. If there is not an antibody of this generation that has the same fitness as the elitist antibody, then copy the elitist antibody saved in the specified variable to the population and delete the antibody with the smallest fitness from the population; otherwise, continue.

Step 6: If the largest fitness of these antibodies of this generation is larger than the fitness of the elitist, then copy the antibody with the largest fitness to the specified variable as the new elitist; otherwise, continue.

Step 7: Compute the concentration of each antibody by Eqs.(8)–(9).

Step 8: Compute the expected reproduction probability of each antibody using Eq.(10) and the selection probability of each antibody by Eq.(11) and then execute selection and reproduction.

Step 9: Execute crossover operations on the population.

Step 10: Execute elitist crossover operations on the population.

Step 11: Produce the next antibody generation by mutation on the population.

Step 12: If the result satisfies the terminal condition, output the result and then stop algorithm; otherwise, return to step 5.

XIV. Conclusion

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of Multidimensional Systems. Digital image processing allows the use of much more complex algorithms for image processing, and hence, can offer both more sophisticated performance at simple tasks, and the implementation of methods which would be impossible by analog.

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