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Linear Model of Resolution and Quality of Digital Images

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Abstract

This paper deals with digital image processing its properties, resolution and quality of such images. Some statistical relations are used to describe images' quality and distributions. Resolution of images is very important in all applications. Probability density function of quality of such images is constructed. It is found that images' quality depends on resolution which takes the form non-linear relation. This paper also presented a linear mathematical model between quality and resolution.

Keywords: digital images, resolution, probability density function

INTRODUCTION

Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter-relationships between objects. They portray spatial information that we can recognize as objects. Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form. In the present context, the analysis of pictures that employ an overhead perspective, including the radiation not visible to human eye are considered, [5].
Digital image processing is an accepted practice in forensic science. It is the position of the Scientific Working Group on Imaging Technologies (SWGIT) that changes to an image made through digital image processing are acceptable in forensic applications provided the following criteria are met:
1. The original image is preserved.

2. The processing steps are logged when they include techniques other than those used in a traditional photographic darkroom.
3. The end result is presented as an enhanced image, which may be reproduced by applying the logged steps to the original image.
4. The recommendations of this document are followed.

Image processing includes:
(1) Image enhancement
(2) Image restoration
(3) Image compression
(4) Image analysis

When using digital image processing techniques one should use caution to avoid (1) introduction of unexplainable artifacts that add misleading information to the image and (2) loss of image detail that could lead to an erroneous interpretation. Any processing techniques should be applied only to the working image.

There are many researches treat this issue: Ioannis G et al. (2005), in this paper an integrated methodology for the detection and removal of cracks on digitized paintings was presented. The cracks are detected by thresholding the output of the morphological top-hat transform. Afterwards, the thin dark brush strokes which have been misidentified as cracks are removed using either a Median Radial Basis Function (MRBF) neural network on hue and saturation data or a semi-automatic procedure based on region growing. Finally, crack filling using order statistics filters or controlled anisotropic diffusion is performed. The methodology has been shown to perform very well on digitized paintings suffering from cracks.

Vasant M. et al.2008, discussed MRI Segmentation assumes great importance research and clinical applications. There are many methods that exist to segment the brain. Of these, conventional methods that use pure image processing techniques are not preferred because they need human interaction for accurate and reliable segmentation. Unsupervised methods, on the other hand, do not require any human interference and can segment the brain with high precision. For this reason, unsupervised methods are preferred over conventional methods. Many unsupervised methods such as Fuzzy c-means; Finite Gaussian Mixture Model, Artificial Neural Networks, etc. exist. In this project, they considered two such unsupervised methods based on FCM and FGMM. Results show that FCM performs better in terms of computational complexity and accuracy, while FGMM has advantages such as learning the number of classes automatically. They observed that FGMM is very sensitive to external parameters d0 and threshold T and an accurate method to determine these parameters based on the image being segmented yields better results.[2].

Image Processing

A digital remotely sensed image is typically composed of picture elements (pixels) located at the intersection of each row i and column j in each K bands of imagery. Associated with each pixel is a number known as Digital Number (DN) or Brightness Value (BV), that depicts the average radiance of a relatively small area within a scene (Fig. 1). A smaller number indicates low average radiance from the area and the high number is an indicator of high radiant properties of the area. The size of this area effects the reproduction of details within the scene. As pixel size is reduced more scene detail is presented in digital representation. These images are represented in digital form. When represented as numbers, brightness can be added, subtracted, multiplied, divided and, in general, subjected to statistical manipulations that are not possible if an image is presented only as a photograph. Although digital analysis of remotely sensed data dates from the early days of remote sensing, the launch of the first Land sat earth observation satellite in 1972 began an era of increasing interest in machine processing (Cambell, 1996 and Jensen, 1996). Previously, digital remote sensing data could be analyzed only at specialized remote sensing laboratories. Specialized equipment and trained personnel necessary to conduct routine machine analysis of data were not widely available, in part because of limited availability of digital remote sensing data and a lack of appreciation of their qualities.

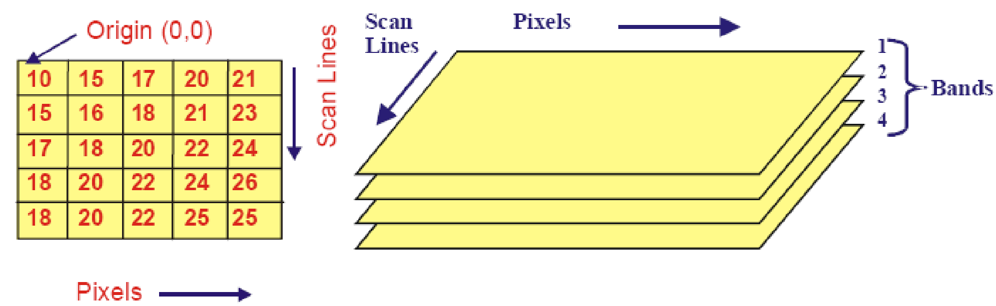

Fig. 1 image processing bands and pixles

Images Resolution/threshold

Increasing resolution enables the capture of finer detail. At some point, however, added resolution will not result in an appreciable gain in image quality, only larger file size. The key is to determine the resolution necessary to capture all significant detail present in the source document.

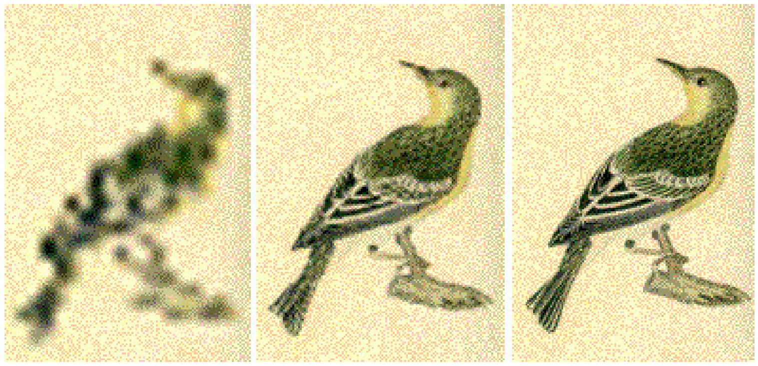

Fig. 2 image resolution

Effects of Resolution on Image Quality: As the resolution increases, the gain in image quality levels off. The threshold setting in bitonal scanning defines the point on a scale, ranging from 0 (black) to 255 (white), at which the gray values captured will be converted to black or white pixels. Note the effect of varying the threshold on typescript scanned at the same resolution on the same scanner. One technique used in image processing implemented is a method for unsupervised segmentation of brain tissues from MR image without any prior knowledge about the number of tissues and their density distributions on each MRI echo. The brain tissues are described by a Finite Gaussian Mixture Model (FGMM). It assumes that the entire image can be expressed as overlaps of Gaussian distributions of its features. The FGMM parameters are learned by sequentially applying the Expectation Maximization (EM) algorithm to a stream of data sets which are specifically organized according to the global spatial relationship of the brain tissues. Assume the finite number of tissues as g, and each tissue can be modeled as one Gaussian. X is a 2 dimensional feature vector. The whole image can be assumed as a mixture of g component Gaussian distribution in some unknown proportions $i\,\pi$, i=1,2,…,g. The probability density function of a data point x given the parameters $i\mu$, Σl for l = 1,2,…,g is given by the equation:

$$p_\ell(x|\mu_\ell, \Sigma_\ell) = \frac{1}{(2\pi)^{d/2}|\Sigma_\ell|^{1/2}} e^{-\frac{1}{2}(x-\mu_\ell)^T \Sigma_\ell^{-1}(x-\mu_\ell)} \tag{1}$$

The parameters of the sequentially learned Gaussian components are updated iteratively. EM is run a number of times and a tight bound on $l\,\mu$ and Σl was given as the stopping condition for EM. This was done primarily to force the EM algorithm to converge on the values. The parameters found out by EM iterations were $l\,\mu$, Σl and the proportion αl of individual Gaussian components in the image.

The posterior probability that a pixel *i x* belongs to tissue *i y* given the parameters of the Gaussian *i y* is given by:

$$p(y_i|x_i, \Theta^g) = \frac{\alpha_{y_i}^g p_{y_i}(x_i|\theta_{y_i}^g)}{p(x_i|\Theta^g)} = \frac{\alpha_{y_i}^g p_{y_i}(x_i|\theta_{y_i}^g)}{\sum_{k=1}^{M} \alpha_k^g p_k(x_i|\theta_k^g)} \quad (2)$$

Therefore, in order to classify a pixel as one tissue to which its posterior probability is the maximum of all tissues, the Expectation Maximization algorithm is used to find an estimation of the parameter ^ψ so that the probability of finding pixels classified in one class or the other is maximized. [7]. It can be clearly exploring the global structure of a trans axial image of human brains. It is found that along the saggital direction from left to right, background and tissues fat, bone, gray matter, white matter, and CSF appear in sequence. This suggests that it could be possible to learn Gaussians one after another by input subsets one by one along the direction. Therefore, instead of working on the entire image, the algorithm works on sequence of subsets so that the method can learn the number of classes automatically, which is a clear plus point when compared to FCM, where the number of classes is a user input.

The learning procedure can be described now: [4]

1) Initialize the number of Gaussians as zero, and an empty processing data set, choose the criteria for judging unclassified data points.

2) Input a subset of data into processing data set

3) Classify the current subset of data with previously learned Gaussians. Label and count the unclassified data. If the number of Gaussians is zero, label the entire subset of data as unclassified

4) If the number of unclassified data points is greater than some threshold (T), add one Gaussian with the initial mean equal to the center of all unclassified data points

5) Use EM algorithm to estimate parameters for the current Gaussians from the current processing data set

6) If all subsets of data are processed, stop otherwise, go to 2) A data point will be unclassified if (min *d*ij) ≥ *d*0 for i=1 to g And as we explained earlier, classification to a particular class is based on the posterior probability values. The Gaussian with the maximum posterior probability will be the class the data point is assigned to.

Results and discussion

The quality of image depends mainly on the resolution, figure (3) shows the relation between image quality and resolution, it is clear that as resolution increases the image quality non-linearly increases but at some specific resolution the quality has a steady-state value.

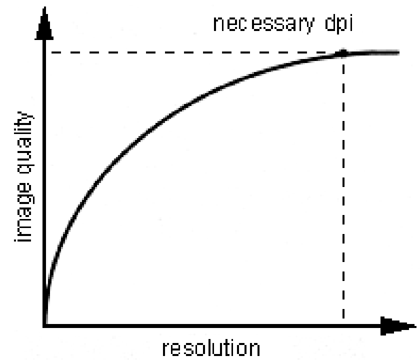

Fig.3 image quality vs. resolution

Linear model for the resolution (dpi) can be expressed as:

$$dpi = \frac{3Q1}{0.39h} \tag{3}$$

Where Q1: is the required quality, h: is the height of the image.
From equation (3) the quality can be expressed as

$$Q1 = 0.13h * dpi \tag{4}$$

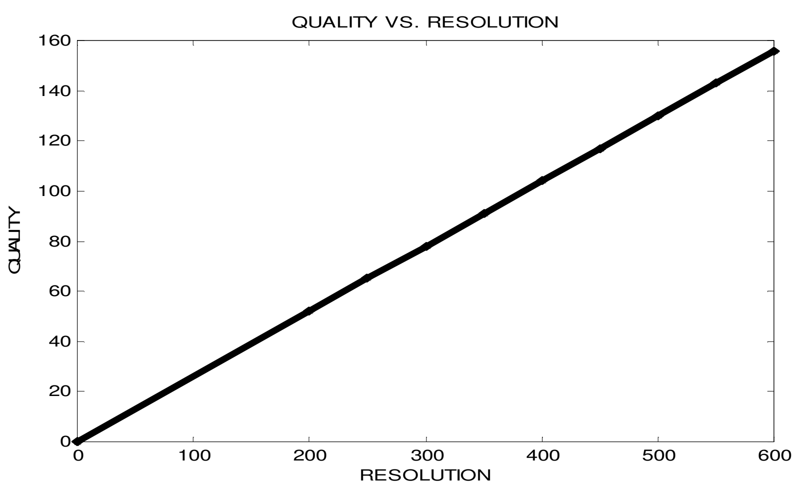

Fig.4 linear model between image quality and resolution

Fig.4 shows the modified linear relationship between image quality and resolution.

Conclusion

It is clear that the quality of the images is a very important in understanding and visualizing and analyze such pictures, the quality of such images is directly depends on resolution of the image.

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