International Journal of Research in Advent Technology (IJRAT) Special Issue
E-ISSN: 2321-9637
Available online at www.ijrat.org
*International Conference "*INTELINC 18*", 12th & 13th October 2018*

Discrete Tomography with Gray Value Estimation

M.Anantha Lakshmi [1],Dr. Prof. P. Kailasapathi [2], Dr.A. Sanjeevi Kumar [3]

1(Electronics and Communication Engineering /Meenakshi College of Engineering,India)
2*(Electrical Engineering / Annamalai University,India)*
3(Electronics and Communication Engineering /Meenakshi Academy of Higher Education and Research,India)

Abstract- TVR-DART with mechanized dim esteem estimation. This calculation is more strong and robotized than the first DART calculation and is gone for imaging of articles comprising of just a couple of various material organizations, each comparing to an alternate dark incentive in the remaking.

1. INTRODUCTION

COMPUTED TOMOGRAPHY

1. Computed Tomography (CT)

Although also based on the variable absorption of x rays by different tissues, computed tomography (CT) imaging, also known as "CAT scanning" (Computerized Axial Tomography), provides a different form of imaging known as cross-sectional imaging. The origin of the word "tomography" is from the Greek word "tomos" meaning "slice" or "section" and "graphe" meaning "drawing." A CT imaging system produces cross-sectional images or "slices" of anatomy, like the slices in a loaf of bread. The cross-sectional images are used for a variety of diagnostic and therapeutic purposes.

1. A motorized table moves the patient through a circular opening in the CT imaging system.
2. As the patient passes through the CT imaging system, a source of x rays rotates around the inside of the circular opening. A single rotation takes about 1 second. The x-ray source produces a narrow, fan-shaped beam of x rays used to irradiate a section of the patient's body The thickness of the fan beam may be as small as 1 millimeter or as large as 10 millimeters. In typical examinations there are several phases; each made up of 10 to 50 rotations of the x-ray tube around the patient in coordination with the table moving through the circular opening. The patient may receive an injection of a "contrast material" to facilitate visualization of vascular structure.
3. Detectors on the exit side of the patient record the x rays exiting the section of the patient's body being irradiated as an x-ray "snapshot" at one position (angle) of the source of x rays. Many different "snapshots" (angles) are collected during one complete rotation.
4. The data are sent to a computer to reconstruct all of the individual "snapshots" into a cross-sectional image (slice) of the internal organs and tissues for each complete rotation of the source of x rays.

2. TOMOGRAPHY

Tomography is imaging by sections or sectioning, through the use of any kind of penetrating wave. The methodis used in radiology, archaeology, biology, atmospheric science, geophysics, oceanography, plasma physics, materials science, astrophysics, quantum information, and other areas of science. The word *tomography* is derived from Ancient Greek τόμος *tomos*, "slice, section" and γράφω *graphō*, "to write" (see also Etymology). A device used in tomography is called a **tomograph**, while the image produced is a **tomogram**.In many cases, the production of these images is based on the mathematical procedure tomographic reconstruction, such as X-ray computed tomography technically being produced from multiple projectional radiographs. Many different reconstruction algorithmsexist. Most algorithms fall into one of two categories: filtered back projection (FBP) and iterative reconstruction (IR). These procedures give inexact results: they represent a compromise between accuracy and computation time required. FBP demands fewer computational resources, while IR generally produces fewer artifacts (errors in the reconstruction) at a higher computing cost

3. GRAY VALUE ESTIMATION

Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called *bilevel* or *binary images*). Grayscale images have many shades of gray in between.

4. EXISTING SYSTEM

Existing algorithms under noisy conditions from a small number of projection images and/or from a small angular range.

5. PROPOSED SYSTEM

The new algorithm requires less effort on parameter tuning compared with the original DART algorithm. With TVR-DART, we aim to provide the tomography society with a easy-to-use and robust algorithm for DT.Electron tomography data sets show thatTVR-DART is capable of providing more accurate reconstruction

6. IMAGE RECONSTRUCTION

Image reconstruction is the creation of a two- or three-dimensional image from scattered or incomplete data such as the radiation readings acquired during a medical imaging study. For some imaging techniques, it is necessary to apply a mathematical formula to generate a readable and usable image or to sharpen an image to make it useful. In computed tomography (CT) scanning, for example, image reconstruction can help generate a three-dimensional image of the body from a series of individual camera images.

Several issues pose a problem with image reconstruction. The first is noise meaningless data that can interrupt the clarity of an image. In medical imaging, noise can occur as a result of patient movement, interference, shadowing and ghosting. For example, one structure in the body might overshadow another and make it hard to spot. Filtration for noise is one aspect of image reconstruction.

Another issue is scattered or incomplete data. With something such as an X-ray, the image is taken in one film exposure, where X-rays pass through the area of interest and create an image. In other techniques, a patient might be bombarded with radiation or subjected to a magnetic field, generating a substantial amount of data that needs to be assembled to create a picture. The immediate output is not readable or meaningful to a human, and it needs to be passed through an algorithm to generate a picture.

7. COMPRESSIVE SENSING

Compressed Sensing is to recover 'high dimensional' signals from the mere knowledge 'low-dimensional' measurements. To state such a problem in its full generality, we assume that the signals **x**live in a signal space and that they are sampled to produces measurements living in a measurement space. We call the map the measurement map note that it can always be assumed to be subjective by reducing We wish to recover the signal i.e. we wish to find a reconstruction map such that.. Since a linear map cannot be injective, the reconstruction identity cannot be valid for all signals. Instead, we impose the signals to belong to a recoverable class Typically, the latter class is taken to be the set of all s-sparse vectors, i.e. the set of all vectors with no more than s nonzero components.

1. Minimal Number of Measurements

Given a sparsity level s, we want to know how few measurements are necessary to recovers-sparse vectors. This depends on the signal and measurement spaces and on thepossible restrictions imposed on the measurement and reconstruction maps. Inothers words, We shall distinguish several cases according to the underlying fields of the signal andmeasurement spaces.

2. Totally Positive Matrices

A square matrix M is called totally positive, resp. totally nonnegative, ifdet(MI;J) > 0; resp. det(MI;J) _ 0; for all index sets I and J of same cardinality. Here MI;J represents the submatrix of M formed by keeping the rows indexed by I and the columns indexed by J.Let us now suppose that m = 2s. We consider an totally positive matrix M, fromwhich we extract m rows indexed by a set I to form an m_N submatrix A. For each indexset J of cardinality m = 2s, the submatrix AJ := MI;J is invertible. Therefore, for anynonzero 2s-sparse vector,.This establishes Condition . Thus, the linear in particular,continuous and antipodal measurement map defined by f(x) = Ax allows reconstructionof every s-sparse vector from m = 2s measurements. This completes our proof, so long as we can exhibit a totally positive matrix M. We takethe classical example of a Vandermonde matrix.

3.Reed-Solomon Decoding

If the m_N matrix A is obtained from an totally positive matrixby selecting m of its rows, then the measurement map defined by f(x) = Ax,allows to reconstruct every s-sparse vector with only m = 2s measurements. In this case,the reconstruction map is given by to find g(y) in a straightforward way, it is required to perform a combinatorial searchwhere alloverdetermined linear systems, have to be solved. Thisis not feasible in practice. In this chapter, we shall introduce a practical reconstructionprocedure that seems to do the job with only m = 2s measurements. This procedure,however, has important faults that we shall expose.

8. IMAGE SEGMENTATION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/orchange the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

APPLICATIONS

Volume segmentation of a 3D-rendered CT scan of the thorax: The anterior thoracic wall, the airways and the pulmonary vessels anterior to the root of the lung have been digitally removed in order to visualize thoracic

THRESHOLDING

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. There is also a balanced histogram thresholding.The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering.Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image.

New methods suggested the usage of multi-dimensional fuzzy rule-based non-linear thresholds. In these works decision over each pixel's membership to a segment is based on multi-dimensional rules derived from fuzzy logic and evolutionary algorithms based on image lighting environment and application.

CLUSTERING METHODS

Image after running k-means with $k = 16$. Note that a common technique to improve performance for large images is to downsample the image, compute the clusters, and then reassign the values to the larger image if necessary

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is

1. Pick K cluster centers, either randomly or based on some heuristic method, for example K-means++
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

HISTOGRAM – BASED METHODS

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Coloror intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This operation is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image.

Histogram-based approaches can also be quickly adapted to apply to multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per-pixel basis where the resulting information is used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in video tracking.

1. Cumulative histogram

A cumulative histogram is a mapping that counts the cumulative number of observations in all of the bins up to the specified bin. That is, the cumulative histogram M_i of a histogram m_j is defined as:

Mi = Σ mj

2. Number of bins and width

There is no "best" number of bins, and different bin sizes can reveal different features of the data. Grouping data is at least as old as Graunt's work, but no systematic guidelines were given until Sturges's work. Using wider bins where the density of the underlying data points is low reduces noise due to sampling randomness; using narrower bins where the density is high (so the signal drowns the noise) gives greater precision to the density estimation. Thus varying the bin-width within a histogram can be beneficial. Nonetheless, equal-width bins are widely used.

Some theoreticians have attempted to determine an optimal number of bins, but these methods generally make strong assumptions about the shape of the distribution. Depending on the actual data distribution and the goals of the analysis, different bin widths may be appropriate, so experimentation is usually needed to determine an appropriate width. There are, however, various useful guidelines and rules of thumb.[

The number of bins *k* can be assigned directly or can be calculated from a suggested bin width *h* as:

K = [max x – min x / h]

The braces indicate the ceiling function.

3. Square-root choice

k = n

which takes the square root of the number of data points in the sample (used by Excel histograms and many others).

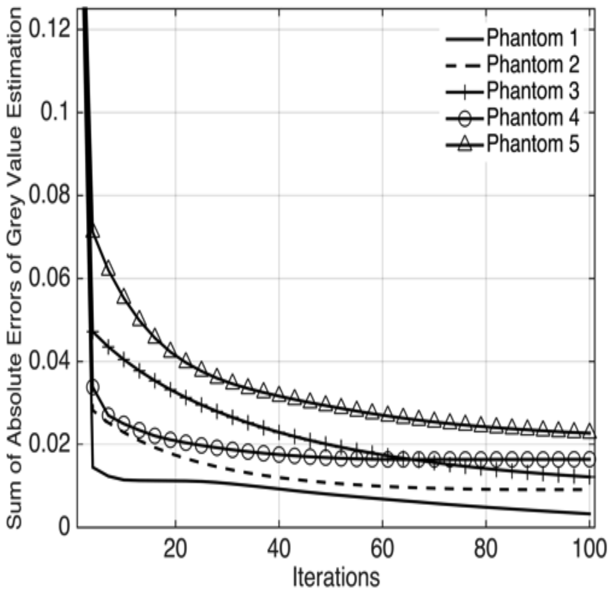
3.Sturges' formula

Sturges' formula[11] is derived from a binomial distribution and implicitly assumes an approximately normal distribution.

K = [log2 + 1]

It implicitly bases the bin sizes on the range of the data and can perform poorly if $n < 30$, because the number of bins will be small—less than seven—and unlikely to show trends in the data well. It may also perform poorly if the data are not normally distributed.

9. RESULTS AND DISCUSSION



Convergence of gray value estimation assume of absolute errors of the estimated gray values through iterations.

10. CONCLUSIONS

The algorithm is aimed at tomographic reconstruction of objects consisting of a few different material compositions, each approximately corresponding to a constant gray value in the reconstruction. By defining a soft segmentation function within the objective function of the reconstruction algorithm, TVR-DART smoothly steers the solution toward discrete Gray values while minimizing the total variation of the boundaries of the discrete solution.

ACKNOWLEDGMENTS

The authors would like to thank Department of Electrical Engineering, Faculty of Engineering and Technology, Annamalai University, Annamalai Nagar for his support within our joint project. They thank Electronics and Communication, Meenakshi Academy of Higher Education and Research, Chennai-78.They thank Electronics and Communication ,Meenakshi College of Engineering.

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