

STRONG ALGORITHM FOR DISCRETE TOMOGRAPHY WITH GRAY VALUE ESTIMATION

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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.

INTRODUCTION

COMPUTED TOMOGRAPHY

1.Conventional X-ray Images

All x-ray imaging is based on the absorption of x rays as they pass through the different parts of a patient's body. Depending on the amount absorbed in a particular tissue such as muscle or lung, a different amount of x rays will pass through and exit the body. The amount of x rays absorbed contributes to the radiation dose to the patient. During conventional x-ray imaging, the exiting x rays interact with a detection device (x-ray film or other image receptor) and provide a 2-dimensional projection image of the tissues within the patient's body - an x-ray produced "photograph" called a "radiograph." The chest x ray is the most common medical imaging examination. During this examination, an image of the heart, lungs, and other anatomy is recorded on the film.

2.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.

TOMOGRAPHY

Tomography is imaging by sections or sectioning, through the use of any kind of penetrating wave. The method is 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 algorithms exist. 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.[1]

Although MRI and ultrasound are transmission methods, they typically do not require movement of the transmitter to acquire data from different directions. In MRI, both projections and higher spatial harmonics are sampled by applying spatially-varying magnetic fields; no moving parts are necessary to generate an image. On the other hand, since ultrasound uses time-of-flight to spatially encode the received signal, it is not strictly a tomographic method and does not require multiple acquisitions at all.

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.

EXISTING SYSTEM

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

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 that TVR-DART is capable of providing more accurate reconstruction

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.

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 live in a signal space and that they are sampled to produce 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 recover s -sparse vectors. This depends on the signal and measurement spaces and on the possible restrictions imposed on the measurement and reconstruction maps. In other words, We shall distinguish several cases according to the underlying fields of the signal and measurement spaces.

2. Totally Positive Matrices

A square matrix M is called totally positive, resp. totally nonnegative, if $\det(M_{I;J}) > 0$; resp. $\det(M_{I;J}) \geq 0$; for all index sets I and J of same cardinality. Here $M_{I;J}$ 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 , from which we extract m rows indexed by a set I to form an $m \times n$ submatrix A . For each index set J of cardinality $m = 2s$, the submatrix $A_J := M_{I;J}$ is invertible. Therefore, for any nonzero $2s$ -sparse vector, This establishes Condition . Thus, the linear in particular, continuous and antipodal measurement map defined by $f(x) = Ax$ allows reconstruction of every s -sparse vector from $m = 2s$ measurements. This completes our proof, so long as we can exhibit a totally positive matrix M . We take the classical example of a Vandermonde matrix.

3. Reed-Solomon Decoding

If the $m \times n$ matrix A is obtained from an totally positive matrix by 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 search where all overdetermined linear systems, have to be solved.

This is not feasible in practice. In this chapter, we shall introduce a practical reconstruction procedure that seems to do the job with only $m = 2s$ measurements. This procedure, however, has important faults that we shall expose.

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/or change 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 .

COMPRESSION BASED METHODS

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modelled by a probability distribution function and its coding length is computed as follows:

1. The boundary encoding leverages the fact that regions in natural images tend to have a smooth contour. This prior is used by Huffman coding to encode the difference chain code of the contours in an image. Thus, the smoother a boundary is, the shorter coding length it attains.
2. Texture is encoded by lossy compression in a way similar to minimum description length (MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modeled by a multivariate normal distribution whose entropy has a closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize.

For any given segmentation of an image, this scheme yields the number of bits required to encode that image based on the given segmentation. Thus, among all possible segmentations of an image, the goal is to find the segmentation which produces the shortest coding length. This can be achieved by a simple agglomerative clustering method. The distortion in the lossy compression determines the coarseness of the segmentation and its optimal value may differ for each image. This parameter can be estimated heuristically from the contrast of textures in an image. For example, when the textures in an image are similar, such as in camouflage images, stronger sensitivity and thus lower quantization is required.

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. Color or 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:

$$M_i = \sum m_j$$

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.¹

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

$$K = \lceil \max x - \min x / h \rceil$$

The braces indicate the ceiling function.

3.Square-root choice

$$k = \sqrt{n}$$

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

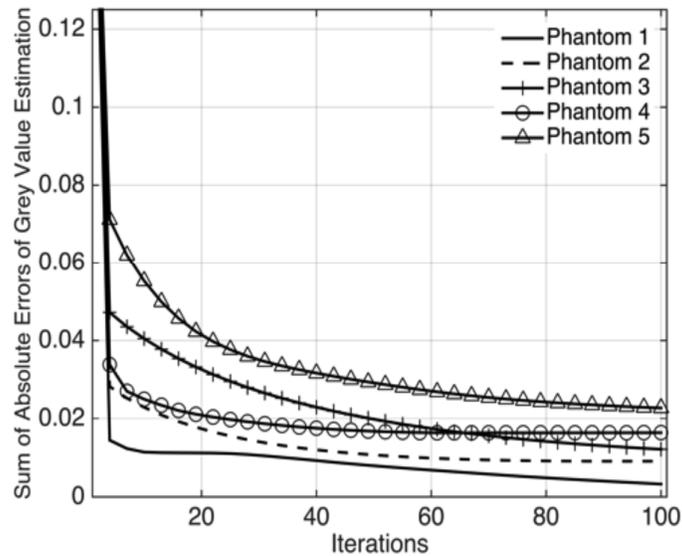
3.Sturges' formula

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

$$K = \lceil \log_2 n + 1 \rceil$$

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.

RESULTS AND DISCUSSION



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

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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