RUN-LENGTH ENCODING FOR VOLUMETRIC TEXTURE

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ABSTRACT

With the dramatic increase of 3D imaging techniques, there is a great demand for new approaches in texture analysis of volumetric data. In this paper, we present a new approach for volumetric texture analysis using a run-length encoding matrix and its texture descriptors. We experiment with our approach on the volumetric data generated from two normal Computed Tomography (CT) studies of the chest and abdomen. Our preliminary results show that there are run-length features calculated from the volumetric run-length matrix that are capable of capturing the texture primitives' properties for different structures in 3D image data, such as the homogeneous texture structure of the liver.

KEY WORDS

Image processing and analysis, volumetric texture, run-length encoding, and texture features.

1. Introduction

Texture is one of the most used characteristics in medical image interpretation, and is applicable to a wide variety of image processing problems. For example, it is difficult to classify human body organ tissues using shape or gray level information because the shape of each organ is not consistent throughout all slices of a 3D medical image and the gray level intensities overlap considerably for soft tissues. However, tissues are expected to have consistent and homogeneous textures along the series of slices forming the 3D image, while being different for various tissues. Therefore, texture information can be used to discriminate among different organ tissues [1].

Over the past several years, there has been an increase in 3D imaging equipment, particularly in the medical field. However, even when sufficient volume data are available, human analysis and visualization of volume data are often difficult due to the limits of human perception; consequently, a good amount of data content is often overlooked. Computerized analysis offers the exciting option of using the entire 3D data set without being limited by 2D perception [2].

While texture analysis for 2D image data has been studied extensively and many algorithms have been developed to deal with 2D texture (statistical moments, co-occurrence matrices, run-length encoding, spectral measures, wavelets, etc.), the study of the characterization and estimation of volumetric textures for 3D image data is still in its early stages [3]. We are currently exploring the advantages and limitations of quantifying the texture information in 3D medical image data [4],[5] and its applications to tissue classification.

In this paper, we present our preliminary results on using run-length statistics for volumetric texture characterization. Using a set of 344 coronal slices from two normal computed tomography (CT) studies, we show that there are run-length features calculated from the volumetric run-length matrix that are capable of capturing the texture primitives' properties for different structures in 3D image data, such as the homogeneous texture structure of the liver.

This paper is organized into six sections. Section 2 provides background information related to the traditional run-length matrices calculated for 2D data. Section 3 describes our approach for run-length encoding for volumetric texture, and Section 4 presents our preliminary results. Section 5 presents the conclusions and Section 6 presents potential future work in the area of volumetric texture in the medical field.

2. Background

When examining medical images, it is often necessary to interpret tissue appearance based on different characteristics such as smoothness, grain, regularity, and homogeneity. These attributes are related to the local intensity variations and can be captured by using various texture metrics [2].

Run-length statistics capture the coarseness of a texture in specified directions. A run is defined as a string of consecutive pixels which have the same gray level intensity along a specific linear orientation. Fine textures tend to contain more short runs with similar gray level intensities, while coarse textures have more long runs with significantly different gray level intensities [6].

A run-length matrix P is defined as follows: each element P*(i, j)* represents the number of runs with pixels of gray level intensity equal to *i* and length of run equal to *j* along a specific orientation. The size of the matrix P is *n* by *k*, where *n* is the maximum gray level in the CT image and *k* is equal to the possible maximum run length in the corresponding image. An orientation is defined using a displacement vector *d(x, y)*, where *x* and *y* are the displacements for the x-axis and y-axis, respectively. The typical orientations are 0°, 45°, 90°, and 135°, and calculating the run-length encoding for each direction will produce four run-length matrices. Table 1 shows the four directions and the corresponding displacement vectors.

Table 1: Displacement representation for 2D run-length matrices

Direction	Vector representation of the displacement: d(x, y)
0^o	(1,0)
45^o	(1,1)
90^o	(0, 1)
135^o	(-1, 1)

Once the run-length matrices are calculated along each direction, several texture descriptors are calculated to capture the texture properties and differentiate among different textures [7]. These descriptors can be used either with respect to each direction or by combining them if a global view of the texture information is required. Eleven descriptors are typically extracted from the run-length matrices: short run emphasis (SRE), long run emphasis (LRE), high gray-level run emphasis (HGRE), low gray-level run emphasis (LGRE), pair-wise combinations of the length and gray level emphasis (SRLGE, SRHGE, LRLGE, LRHGE), run-length non-uniformity (RLNU), grey-level non-uniformity (GLNU), and run percentage (RPC). Some of these descriptors reflect specific characteristics in the image. For example, SRE measures the distribution of short runs in an image, while run percentage measures both the homogeneity and the distribution of runs of an image in a specific direction. The formulas for calculating the descriptors and their interpretation are provided in an Appendix of this paper.

3. Run-Length Encoding for Volumetric Texture

We present a new approach for calculating run-length encoding matrices for volumetric texture that will allow capturing the coarseness characteristic of the texture in 3D image data.

For a given 3D image, presented as a series of slices in a preferred slice orientation, a run-length matrix P is defined as follows: each element P*(i, j)* represents the number of runs with pixels of gray level intensity equal to *i* and length of run equal to *j* along the *d(x, y, z)* direction. As for the 2D run-length encoding, the size of the matrix P is *n* by *k*, where *n* is the maximum gray level n in the CT image and *k* is equal to the possible maximum run length in corresponding image. An orientation is defined using a displacement vector *d(x, y, z)*, where *x, y, z* are the displacements for the x-axis, y-axis, and z-axis, respectively. Unlike the 2D texture characterization, the volumetric texture requires 13 different displacements from a total of 26 possible displacements in a three dimensional space; Table 2 shows the thirteen displacement vectors.

Table 2: Displacement representation for run-length matrices for volumetric data

Direction (θ, ϕ)	Vector representation of the displacement: d(x, y, z)
$(0^o, 45^o)$	(1, 0, 1)
$(0^o, 90^o)$	(1, 0, 0)
$(0^o, 135^o)$	(1, 0, -1)
$(45^o, 45^o)$	(1, 1, 1)
$(45^o, 90^o)$	(1, 1, 0)
$(45^o, 135^o)$	(1, 1 -1)
$(90^o, 45^o)$	(0, 1, 1)
$(90^o, 90^o)$	(0, 1, 0)
$(90^o, 135^o)$	(0, 1, -1)
$(135^o, 45^o)$	(-1, 1, 1)
$(135^o, 90^o)$	(-1, 1, 0)
$(135^o, 135^o)$	(-1, 1, -1)
$(-, 0^o)$	(0, 0, 1)

Furthermore, each slice does not need to be processed individually, as is the case of calculating the run-length encoding for 2D data; all slices are processed at once producing only one run-length encoding matrix for all consecutive slices forming the 3D image, and thus, the run-length computation for the volumetric texture is faster.

The same eleven descriptors defined for the 2D texture can also be calculated for the run-length matrices for volumetric data using the same formulas from the appendix.

4. Methods and Preliminary Results

4.1 Data Description

In order to evaluate the feasibility of our approach for the medical domain, we implemented the proposed approach on 3D data obtained from two normal CT studies[1]. The 3D DICOM[2] image data consists of consecutive 2D slices, each slice being 512 by 512 pixels in size and having 16-bit gray level resolution. Since one of the goals of our research is to classify organ tissues using volumetric texture, we calculated the texture

[1] The the images were provided by the Northwestern Memorial Hospital (NMH) as part of the collaborative research project*: Classification of tissues in CT studies.*

[2] DICOM stands for Digital Imaging and Communications in Medicine; it is a standard format for medical images.

descriptors for the organs segmented from these CT studies. Using the Active Contour Mapping (ACM) algorithm [8], we segmented five organs from 344 coronial slices: backbone, kidneys, liver, spleen and heart (Table 3). Figure 1 shows an overview of the entire process we performed in order to derive our results.

Table 3: Summary of the segmented slices per patient

	Patient 1	Patient 2
Organ	# of slices	# of slices
Backbone	68	72
Heart	27	25
Kidneys (L and R)	27	27
Liver	29	29
Spleen	20	20
Total Slices	171	173

4. 2 Two-Dimensional Run-length Matrices

We calculated a two-dimensional run-length encoding as a basis for the comparison with our proposed method.

First, we quantized the gray levels into 32 gray levels using linear mapping. As mentioned in Section 1, the number of rows in the run-length matrix is given by the gray-level resolution of the DICOM image; if many gray-level intensities are used, many runs would contain only one pixel and therefore, it is necessary to group the gray levels into bins. Research literature on this topic shows that usually 16 gray levels are sufficient for discrimination or segmentation of textures [9] for 8-bit gray level images. Since we are dealing with CT scans, in which the maximum gray level values is 2^{16}, we chose to use 32 bins rather than 16 bins in order to increase the discriminating power of the run-length matrices. Moreover, for reasons of computational efficiency, we further reduced the size of run-length matrices by grouping the length of runs into bins logarithmically, so each bin a contains all runs of length 2^ (a-1) + 1 through 2^a, with a greater than zero.

For each region containing a segmented organ from the DICOM slice, we calculated the 2D run-length matrix in each one of the four directions shown in Table 1.

Then, for each of the four matrices, we extracted the eleven run-length descriptors; the final value per descriptor was the average of the four values obtained from the four orientations.

4. 3 Volumetric Run-length Matrices

To apply our proposed run-length encoding algorithm for volumetric data, we quantized gray levels and binned the run lengths in the same way we did for the 2D data. Using volumetric data, we obtained one run-length encoding matrix per organ and per direction since all consecutive slices were considered one input for the volumetric texture calculation in each direction (see Figure 2). An important fact to notice here is that the number of matrices for each organ is fixed, even though the number of slices for each organ may vary.

Therefore, we obtained thirteen run-length matrices per organ because of the thirteen directions in the 3D space as illustrated in Table 2. We extracted the eleven run-length descriptors from each of these thirteen matrices and then we calculated the average value for the thirteen values per organ and per descriptor.

We compared the run-length features obtained from 2D data and 3D data. In order to visualize and compare the distribution of each descriptor per organ with respect to the 2D and 3D image data, we created both a histogram and a five-number summary for the 2D data; then we mapped the result for 3D data with respect to the five-number summary for the 2D data and compared the values for the two sets. Table 4 shows how many descriptors fall within the range of the first and third quartile for the 2D data and how many fall within the range of the minimum and maximum.

Our preliminary results show that there are two descriptors (HGRE and LGRE) whose values for the 3D data fall within the range of 1st quartile (Q_1) and 3rd quartile (Q_3) of 2D data for each organ; moreover, the 3D values are very close to the median of the 2D texture values. The results confirm the interpretation of these two descriptors derived from their definitions: HGRE and LGRE capture only the gray level intensity of the texture primitives without taking into account the shape properties of the gray level primitives. On the other hand, the SRE descriptor does not match its corresponding descriptor for the 2D data; it is out of the range of the minimum and maximum for the 2D data. The difference in the result for this descriptor can be explained by the fact that SRE only measures the distribution of short runs present in the texture and it does not take into account the gray level intensity at all; therefore, the SRE descriptor is more sensitive to the shape aspect of the gray level primitive, which might be very different in volumetric data than in 2D data. Overall, approximately 33% of 3D run-length features fall in the range of the 1st and 3rd quartiles of 2D run-length features and 58% are within the range of the minimum and maximum, while 42% of the descriptors are out of this range. We did not include

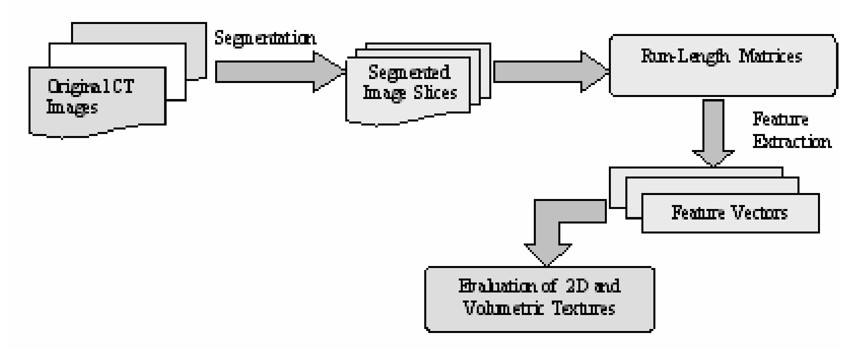
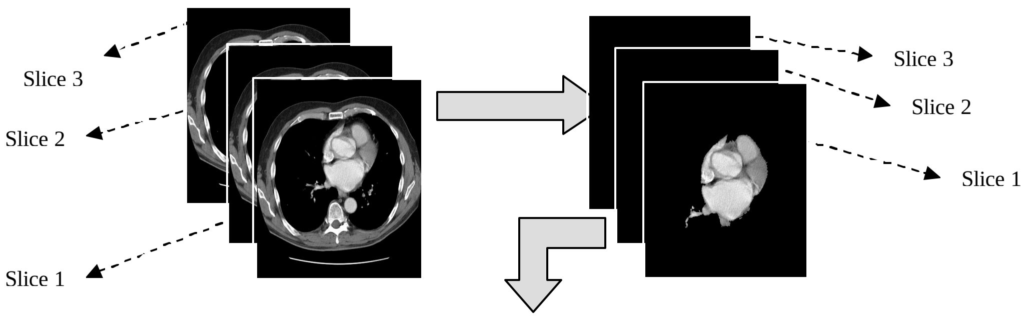


Figure 1: Overview of the 2D and volumetric data calculation and interpretation



SRE	*LRE*	*LGRE*	*HGRE*	*SRLGE*	*SRHGE*	*LRHGE*	*LRLGE*	*GLNU*	*RLNU*	*RPC*
0.625	4.081	0.042	68.84	0.027	40.785	309.825	0.151	55821	123300	0.589

Figure 2: 3D Features for an entire organ (across slices)

Table 4: The distribution of the volumetric run-length descriptors with respect to the 2D data

	# of desc.	$Q_1 - Q_3$	Min-Max
SRE	5	0	0
LRE	5	1	3
LGRE	5	5	5
HGRE	5	5	5
SRLGE	5	0	4
SRHGE	5	2	3
LRHGE	5	1	2
LRLGE	5	1	2
RPC	5	0	2
Total	45	15	26

GLNU and RLNU are not included in our comparisons because the number of runs increases the values of these descriptors in a quadratic fashion.

Another interesting comparison is to look at the behavior of the descriptors for each organ (Table 5). Among the five organs, we noticed that, for the liver, the 3D values for all descriptors are closest to the values for the 2D image data. The explanation of this result is given by the 3D homogeneous structure of the liver across consecutive slices.

Table 5: The distribution of the volumetric run-length descriptors per organ

	# of desc.	$Q_1 - Q_3$	Min-Max
backbone	9	3	5
heart	9	2	6
kidney	9	2	2
liver	9	6	8
spleen	9	2	5
total	45	15	26

5. Conclusion

In this paper we demonstrated a new approach for volumetric data characterization using a set of run-length encoding features. Our preliminary results show that the results obtained from 2D data and those obtained from volumetric data have some similarities as well as differences. The similarities for 2D and volumetric texture data are given by the HGRE and LGRE descriptors. The differences for some of the descriptors might indicate that results obtained from 2D data only reflect the texture information within a CT slice, whereas results obtained from volumetric data represent the texture information across a set of slices. Another factor which might contribute to the difference is that volumetric data is usually viewed as a set of 2D images and the sparseness of the set of slices affects the result for volumetric data since the inter-pixel distance is different from the inter-slice distance. However, the development of new medical hardware, such as new acquisition sensors that will either create dense enough multiple slices or will be able to operate on 3D space directly [3], creates a necessity for techniques that will allow volumetric texture characterization and analysis.

6. Future Work

In this research we presented run-length statistics for the texture analysis of volumetric data in the medical domain. As future work, we are going to further investigate the run-length statistic for volumetric data, and determine the most relevant features among the eleven features presented in this paper. This investigation will allow us to remove the highly correlated features, while keeping the most important ones with respect to their discriminative power.

We will also test our approach on more CT studies, and use and compare the 2D and volumetric results for human tissues' classification in normal CT studies.

As a final goal, we are looking at the successful use of the volumetric texture features presented in this paper along with other texture features suitable for 3D images to develop an automated and reliable system for analysis, classification [10] and segmentation of 3D CT images.

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Appendix

Feature	**Formula**	**What is measured?**
Short Run Emphasis	$SRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{j^2}$	Measures the distribution of short runs. The SRE is highly dependent on the occurrence of short runs and is expected large for fine textures.
Long Run Emphasis	$LRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} P(i,j) * j^2$	Measures distribution of long runs. The LRE is highly dependent on the occurrence of long runs and is expected large for coarse structural textures.
Low Gray-Level Run Emphasis	$LGRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2}$	Measures the distribution of low gray level values. The LGRE is expected large for the image with low gray level values.
High Gray-Level Run Emphasis	$HGRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} P(i,j) * i^2$	Measures the distribution of high gray level values. The HGRE is expected large for the image with high gray level values.

Short Run Low Gray-Level Emphasis	$SRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j)}{i^2 * j^2}$	Measures the joint distribution of short runs and low gray level values. The SRLGE is expected large for the image with many short runs and lower gray level values
Short Run High Gray-Level Emphasis	$SRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j) * i^2}{j^2}$	Measures the joint distribution of short runs and high gray level values. The SRHGE is expected large for the image with many short runs and high gray level values
Long Run Low Gray-Level Emphasis	$LRLGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}\frac{p(i,j) * j^2}{i^2}$	Measures the joint distribution of long runs and low gray level values. The LRLGE is expected large for the image with many long runs and low gray level values
Long Run High Gray-Level Emphasis	$LRHGE = \frac{1}{n_r}\sum_{i=1}^{M}\sum_{j=1}^{N}P(i,j) * i^2 * j^2$	Measures the joint distribution of long runs and high gray level values. The LRHGE is expected large for images with many long runs and high gray level values
Gray-Level Non-uniformity	$GLNU = \frac{1}{n_r}\sum_{i=1}^{M}\left(\sum_{j=1}^{N}P(i,j)\right)^2$	Measures the similarity of gray level values through out the image. The GLN is expected small if the gray level values are alike through out the image.
Run Length Non-uniformity	$RLNU = \frac{1}{n_r}\sum_{j=1}^{N}\left(\sum_{i=1}^{M}P(i,j)\right)^2$	Measures the similarity of the length of runs through out the image. The RLN is expected small if the run lengths are alike through out the image.
Run Percentage	$RPC = \frac{n_r}{P(i,j) * j}$	Measures the homogeneity and the distribution of runs of an image in a specific direction. The RPC is the largest when the length of runs is 1 for all gray levels in specific direction.