CO-OCCURRENCE MATRICES FOR VOLUMETRIC DATA

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ABSTRACT

In this paper, we investigate a new approach to the co-occurrence matrix currently used to extract textural features: *co-occurrence matrices for volumetric data*. While traditional texture metrics have concentrated on 2D texture, 3D imaging modalities are becoming more and more prevalent, providing the possibility of examining texture as a volumetric phenomenon. Just as computer graphics have used 3D textures as a more realistic alternative to 2D texture mapping, we expect that texture derived from volumetric data will have better discriminating power than 2D texture derived from slice data. An experimental study has been conducted in which the results for textural features derived from 2D are compared to those results derived from using co-occurrence matrices for volumetric data. Our preliminary experimental results indicate that the volumetric texture features have better discriminating power than 2D texture derived from slice data.

KEY WORDS

Imaging and image processing, co-occurrence matrices, volumetric data, volumetric texture

1. Introduction

Texture is one of the most commonly used features used to analyze and interpret images, specifically medical images. *Texture* is a measure of the variation of the intensity of a surface, quantifying properties such as smoothness, coarseness, and regularity. It is often used as a region descriptor in image analysis and computer vision. Specifically, a textured region consists of a connected set of pixels that satisfy a given gray-level property which occurs repeatedly in an image region [1]. Several methods have been applied towards the analysis and characterization of texture within medical images including fractal dimension, run-length encoding, discrete wavelet transform, and two-dimensional co-occurrence matrices [2]. Of those mentioned, in texture analysis, two-dimensional dependence matrices [co-occurrence matrices] are extensively used; they are able to capture the spatial dependence of gray-levels which contributes to the perception of texture [1].

In this paper, we investigate a new approach to the co-occurrence matrix currently used to extract textural features: *co-occurrence matrices for volumetric data*. While traditional texture metrics have concentrated on 2D texture, 3D imaging modalities are becoming more and more prevalent, providing the possibility of examining texture as a volumetric phenomenon [3]. Just as computer graphics have used 3D textures as a more realistic alternative to 2D texture mapping [4], we expect that texture derived from volumetric data will have better discriminating power than 2D texture derived from slice data. Our goal is to be able to apply these co-occurrence matrices to volumetric data provided by Computerized Tomography (CT) modalities to calculate volumetric texture descriptors that can be used for segmentation and classification of soft tissues in CT studies.

At this point, it is critical to make a clear distinction between our proposed approach and that of 3D co-occurrence matrices. As it is presented in the literature, 3D co-occurrence matrices are calculated by summing pixel triplet probabilities in a 2D image, as opposed to the pixel pair probabilities that are summed in 2D co-occurrence matrices [5]. The *co-occurrence matrices for volumetric texture* that we are introducing in this paper are 2D dependence matrices that are able to capture the spatial dependence of gray-level values in a set of three-dimensional data (i.e. a set of CT scans for a given patient is given as a single three-dimensional input); these co-occurrence matrices are calculated by summing pixel pair probabilities within a 3 dimensional space.

In the next section, the traditional 2D co-occurrence matrix is described, along with our new, proposed approach for volumetric texture. Our experimental results and conclusions are presented in section 3, followed by future work in section 4.

2. Methodology

2.1. Description of Two-dimensional Co-occurrence Matrices

Two-dimensional co-occurrence (gray-level dependence) matrices, proposed by Haralick in 1973, are generally used in texture analysis because they are able to capture the spatial dependence of gray-level values within an image [6]. A 2D co-occurrence matrix, P, is an n x n matrix, where n is the number of gray-levels within an image. For reasons of computational efficiency, the number of gray levels can be reduced if one chooses to bin them, thus reducing the size of the co-occurrence matrix. The matrix acts as an accumulator so that P[*i* , *j*] counts the number of pixel pairs having the intensities *i* and *j*. Pixel pairs are defined by a distance and direction which can be represented by a displacement vector d = (*dx*,*dy*), where *dx* represents the number of pixels moved along the x-axis, and *dy* represents the number of pixels moved along the y-axis of an image slice.

In order to quantify this spatial dependence of gray-level values, we calculate various textural features proposed by Haralick [6, 7], including Entropy, Energy (Angular Second Moment), Contrast, Homogeneity, SumMean (Mean), Variance, Correlation, Maximum Probability, Inverse Difference Moment, and Cluster Tendency. For the formulas and the intuitive interpretations of these features with respect to the texture characterization, we refer the reader to the Appendix section of the paper.

2.2. Description of Our Proposed Approach: Co-occurrence Matrices for Volumetric Data

We present a new approach for calculating co-occurrence matrices: *Co-occurrence Matrices for Volumetric Data*. Co-occurrence matrices for volumetric data are matrices that are able to capture the spatial dependence of gray-level values across multiple slices, whereas the two-dimensional co-occurrence matrices capture the spatial dependence of gray levels within a specific slice (scan). A co-occurrence matrix for volumetric data is an n x n matrix, where n represents the number of gray-levels within an image. For reasons of computational efficiency, the number of gray levels can be reduced if one chooses to bin them, thus reducing the size of the co-occurrence matrix. Like the traditional co-occurrence matrices, this matrix also acts as an accumulator so that P[*i* , *j*] counts the number of pixel pairs having the intensities *i* and *j*. However, this matrix is defined by specifying a displacement d = (*dx, dy, dz*), where *dx* and *dy* are the same as described for 2D co-occurrence matrices, and *dz* represents the number of pixels moved along the z-axis of the three-dimensional image.

We take the new resulting matrices and we quantify the spatial dependence of gray-level values by calculating the 10 Haralick textural features mentioned in the previous subsection, and described in the appendix [6, 7].

3. Preliminary Experimental Results and Conclusions

3.1. Data Description

In order to evaluate our approach, we tested it on a set of 344 coronal CT scans obtained from 2 normal CT studies that were provided by Northwestern Memorial Hospital[1]. Each scan is a 512 x 512 cross-sectional gray-level slice through the human body; the slices are in DICOM[2] format which have up to a 16 bit gray-level resolution.

Since our goal is to calculate the volumetric texture for different organs in the CT scans, as a pre-processing stage, we segmented different regions of interest (backbone, heart, kidney, liver, and spleen) using Active Contours (snakes) [8, 9].

Table 1: Segmented Data Summary

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

A snake is a function that recreates the boundary of a particular object when given a set of initial points around the region of interest, as well as values for parameters that determine the boundary's smoothness. One of the main advantages of using snakes for region segmentation is the capability of the snake approach to segment regions with irregular shapes such as in the case of the backbone.

At the end of the segmentation stage, a stack of slices for each organ per patient is obtained as presented in Table 1. In 2D, each slice within a stack is processed individually, while in 3D each stack forms a single 3D image. Once segmentation is completed, the two approaches are implemented on the image data. The additional steps that are followed in order to compare the discriminative power of the two approaches are presented in Figure 1. The actual implementations of these processes, as well as the results yielded are described in more detail in the upcoming sections.

[1]This project is an ongoing research collaboration between CTI Intelligent Multimedia Processing Laboratory and Northwestern Memorial Hospital

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

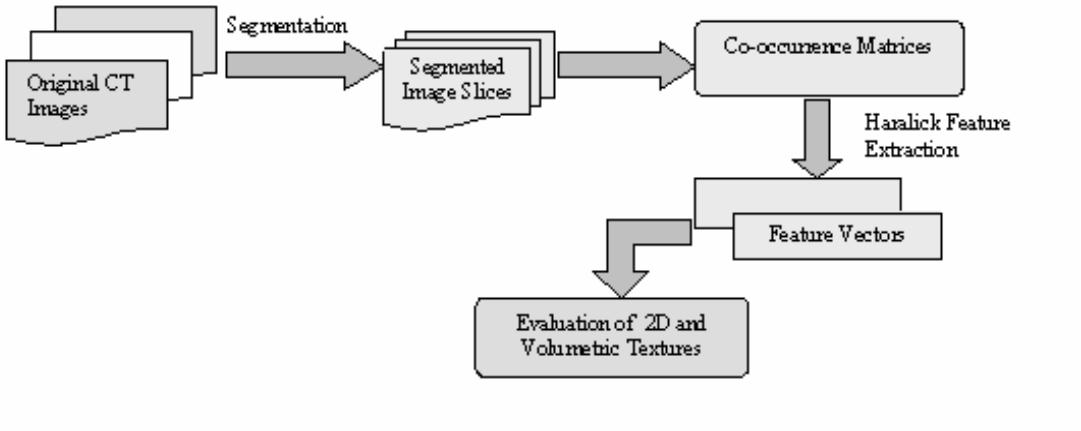


Figure 1: The diagram of the system

3.2. Two-Dimensional Co-occurrence Matrices

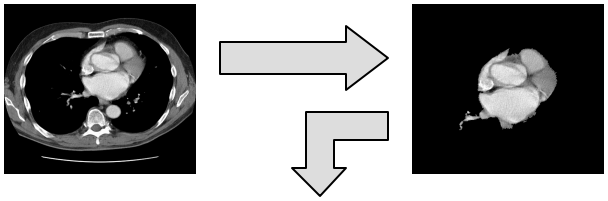
We first implemented a two-dimensional co-occurrence matrix as a basis for comparison with our proposed method. As previously mentioned, the range of gray-level values within a given image determines the dimensions of a two-dimensional co-occurrence matrix. The segmented slices that we are conducting our experiments on, however, have 4096 gray-levels, which would make our co-occurrence matrix 4096 x 4096. A matrix of this size is too large, so we split our gray levels into bins by a straight division of 16 in order to be computationally efficient. Therefore, gray levels from 0 to 15 fall into bin 1, gray levels from 16 to 32 fall into bin 2, and so on, leaving us with 256 bins [10].

We calculated the normalized 2D co-occurrence matrices for each segmented 2D slice using four directions and five distances, giving us 20 different displacement vectors, and thus 20 different matrices for each segmented slice. These displacement vectors (d = (*dx*, *dy*)) are listed in Table 2, and D in the table represents the distance variable with values from 1 pixel to 5 pixels [11].

Table 2: Displacement vectors for 2D data

Direction	Displacement Vector Representation for Direction
0^o	(D,0)
45^o	(D,D)
90^o	(0, D)
135^o	(-D, D)

For each of these 20 matrices we calculated the ten Haralick features that were previously mentioned in Section 2.1. Therefore, 20 values were obtained for each texture descriptor; in order to compare the values for the 2D data with those for volumetric data, the average value per descriptor was calculated for each organ. Figure 2 shows the diagram of the 2D texture descriptors' calculation.



Entropy	Energy	Contrast	Homogeneity	SumMean	Variance	Correlation	Maximum Probability	Inverse Difference Moment	Cluster Tendency
3.93	0.043	7.33	0.55	69.99	21.53	0.072	0.10	0.44	78.78

Figure 2: Feature calculation for 2D data (2D slice of an organ)

Since the texture of a particular human body organ should remain the same regardless of whose body it is located in, we are focusing on inter-organ relationships rather than inter-patient relationships when we evaluate the traditional and the new proposed co-occurrence matrix approaches. Therefore, in order to visualize the discriminative power of the texture descriptors for the two approaches, a histogram was created for each feature and each organ using the mean values for the corresponding organ slices, and combining the data for patient 1 and patient 2. These histograms were automatically generated by SPSS, a statistical software program which allows one to analyze and describe data. Figure 3 shows the histogram for spleen data from both patient 1 and patient 2 (a total of 40 segmented spleen slices. After the calculation of the volumetric descriptors, the volumetric values will be represented on these histograms for interpretation. The visualization of the other features and organs is done in a similar manner.

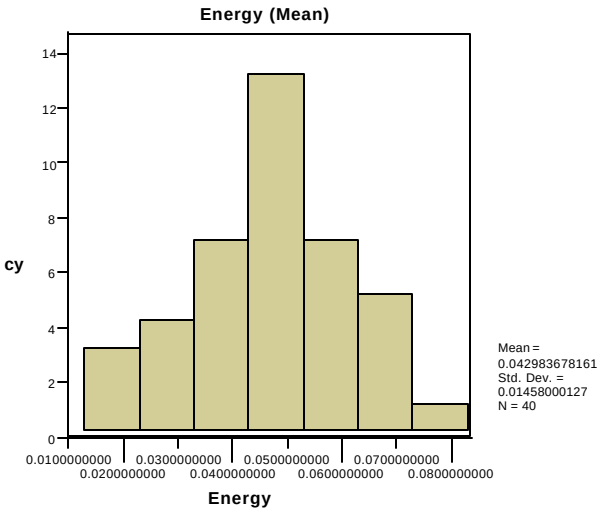


Figure 3: Histogram for the 2D Energy descriptor for the Spleen data

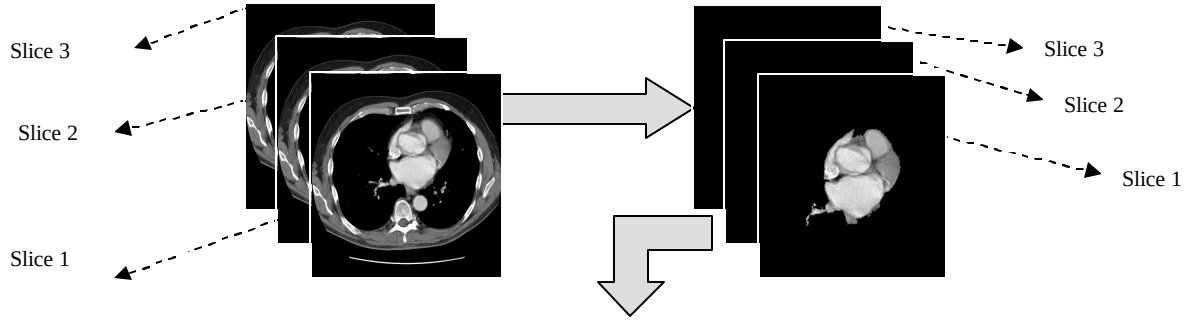
3.3. Co-occurrence Matrices for Volumetric Data

After this basis for our comparison was completed, we implemented our proposed method for the volumetric data. Just as with 2D co-occurrence matrices, these matrices are also two-dimensional and required the gray level values to be reduced to 256 bins in order to be computationally efficient.

In 2D, each slice for a particular organ led to the creation of 20 matrices (four angles and 5 distances) and thus, only for a single organ (such as spleen) hundreds of co-occurrence matrices have to be calculated (20 spleen slices per patient x 20 co-occurrence matrices as shown in Table 1. The number only increases as one moves onto the various other organs since the number of slices segmented out for them is greater.

Using volumetric data, however, there is only one input per organ: a volumetric (3D) image that is comprised of several slices "connected together" by the z-axis. In other words, we view a set of medical scans for a patient as one image that is three-dimensional as shown in Figure 4. We calculated normalized co-occurrence matrices for volumetric data for each of these 3D images. However, now that we have the third dimension, we are no longer just using the four directions and five distances summarized in Table 2. In the volumetric case, there are 26 directions and only 13 are different.

In addition to the 13 directions, we are using 5 distances, which will produce a total of 65 displacement vectors, and thus 65 co-occurrence matrices. Therefore, if θ is measured in the XY plane starting at 0 in the positive x direction, and ϕ is measured "above" and "below" the XY plane, then the 13 directions and their corresponding displacement vectors (d = (*dx*, *dy*, *dz*)) can be described as shown in Table 3 (D = distances from 1 pixel to 5 pixels).



Entropy	Energy	Contrast	Homogeneity	SumMean	Variance	Correlation	Maximum Probability	Inverse Difference Moment	Cluster Tendency
4.25	0.033	17.29	0.47	69.80	13.75	0.025	0.085	0.39	37.72

Figure 4: Feature calculation for volumetric data (an organ across multiple slices)

Table 3: Displacement Vectors for Co-occurrence Matrices for Volumetric Data

Direction (θ, ϕ)	Displacement Vector	Corresponding Duplicate Vector
(0^o, 45^o)	(D, 0, D)	(-D, 0, -D)
(0^o, 90^o)	(D, 0, 0)	(-D, 0, 0)
(0^o, 135^o)	(D, 0, -D)	(-D, 0, D)
(45^o, 45^o)	(D, D, D)	(-D, -D, -D)
(45^o, 90^o)	(D, D, 0)	(-D, -D, 0)
(45^o, 135^o)	(D, D, -D)	(-D, -D, D)
(90^o, 45^o)	(0, D, D)	(0, -D, -D)
(90^o, 90^o)	(0, D, 0)	(0, -D, 0)
(90^o, 135^o)	(0, D, -D)	(0, -D, D)
(135^o, 45^o)	(-D, D, D)	(D, -D, -D)
(135^o, 90^o)	(-D, D, 0)	(D, -D, 0)
(135^o, 135^o)	(-D, D, -D)	(D, -D, D)
(-, 0^o)	(0, 0, D)	(0, 0, -D)

It is important to note *this number of matrices is fixed per organ despite the number slices that were segmented.* Consequently, for the previous example, the number of 400 co-occurrence matrices for 2D spleen data is reduced to 65 matrices for volumetric data.

For each of these 65 matrices per segmented organ, we calculated the same ten Haralick features as we calculated for the 2D co-occurrence matrices. Then, we averaged the 65 values for descriptor per organ and thus, producing a single set of values for the 10 features per organ for each patient. Therefore, for our current data set consisting of two patients, we will have 2 values for each descriptor, one for patient 1 and one for patient 2.

In order to compare the 2D texture features with the volumetric texture features, in addition to using histograms to visualize the relationships between the two sets of features, we examine the values for the volumetric data with respect to the range of the 2D data; this range is given by the maximum and minimum values per descriptor. In doing this, we ask the question: "Does the volumetric data fall within the corresponding ranges of the 2D data?" The results of our analysis are summarized for each feature in Table 4 and for each organ in Table 5.

Table 4: The Distribution of the volumetric data with respect to the 2D data

Features	# of Organs	(Min , Max)
Entropy	5	5
Energy	5	5
Contrast	5	3
Homogeneity	5	3
SumMean	5	5
Variance	5	5
Correlation	5	4
Maximum Probability	5	5
Inverse Difference Moment	5	3
Cluster Tendency	5	5
TOTAL	50	43

Table 5: The Distribution of the volumetric data with respect to 2D organ data

	# of Features.	Min - Max
Backbone	10	10
Heart	10	7
Kidney	10	6
Liver	10	10
Spleen	10	10
TOTAL	50	43

3.4. Conclusion

Our preliminary results are promising, especially given the very small data set. Table 4 shows the number of organs analyzed per feature (column 2), followed by the number of those organs (column 3) whose volumetric results fall within the minimum and maximum of the corresponding 2D data. Overall, we found that 86% of the volumetric feature values fall within the corresponding 2D feature ranges across all organs. Of the 10 Haralick features, we found that Contrast, Homogeneity, and Inverse Difference Moment have the least consistency between the 2D and volumetric data. Each of these features is calculated by a specific difference of intensities in the pixels of the pair, and this differencing is sensitive to the ratio of inter-slice to inter-pixel distance. However, while this difference might be problematic for organ tissue classifiers based on 2D data, we expect that, ultimately, the results obtained using co-occurrence matrices for volumetric data will provide more information about the textures within an organ and therefore, texture derived from volumetric data will have better discriminating power than 2D texture derived from slices.

Table 5 shows the number of features analyzed per organ (column 2), followed by the number of features whose volumetric results fall within the minimum and maximum of the corresponding 2D data (column 3). Of the five organs, we found that the Heart and Kidney have the least consistency between the volumetric data and the 2D data. This inconsistency can be explained by the varying textures within these organs as moving from one slice to the next. While 2D deals with individual slices, and thus separated slice textures, volumetric data ties these textures together; a single value per feature will take into account all textures within a particular organ. We expect that the results obtained using co-occurrence matrices for volumetric data provide more information about the textures within an organ and therefore, texture derived from volumetric data will have better discriminating power than 2D texture derived from slice.

4. Future Work

In this paper, a new approach for volumetric texture characterization has been presented. Based on our preliminary results, we are encouraged to continue our investigation of co-occurrence matrices for volumetric

data and analyze the discriminating power of the texture features derived from them. We plan to perform more tests on the CT scans by either adding more CT scans from different patients or divide the current slices into regions of interest as proposed in [11].

Furthermore, we hope to successfully use the volumetric texture descriptors presented in this paper to build robust classifiers for volumetric textures in CT studies. These classifiers will also allow the development of a texture vocabulary for organs' tissues in terms of low-level texture features derived from pixel data. The texture vocabulary can also be used to enhance several algorithms for object segmentation in CT modalities such as the Snake algorithm used in this paper.

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Appendix

Feature	Formula	What is measured?
Entropy	$-\sum_{i}^{M}\sum_{j}^{N} P[i,j]\log P[i,j]$	Measures the randomness of a gray-level distribution. The Entropy is expected to be high if the gray levels are distributed randomly through out the image.
Energy(Angular Second Moment)	$\sum_{i}^{M}\sum_{j}^{N} P^{2}[i.j]$	Measures the number of repeated pairs. The Energy is expected to be high if the occurrence of repeated pixel pairs is high.
Contrast	$\sum_{i}^{M}\sum_{j}^{N} (i-j)^{2} P[i.j]$	Measures the local contrast of an image. The Contrast is expected to be low if the gray levels of each pixel pair are similar.
Homogeneity	$\sum_{i}^{M}\sum_{j}^{N} \frac{P[i.j]}{1+\lvert i-j\rvert}$	Measures the local homogeneity of a pixel pair. The Homogeneity is expected to be large if the gray levels of each pixel pair are similar
SumMean (Mean)	$\frac{1}{2}\sum_{i}^{M}\sum_{j}^{N} (iP[i,j]+jP[i,j])$	Provides the mean of the gray levels in the image. The SumMean is expected to be large if the sum of the gray levels of the image is high.
Variance	$\frac{1}{2}\sum_{i}^{M}\sum_{j}^{N} ((i-m)^{2}P[i,j]+(j-m)^{2}P[i,j])$	Variance tells us how spread out the distribution of gray-levels is. The Variance is expected to be large if the gray levels of the image are spread out greatly.
Correlation	$\sum_{i}^{M}\sum_{j}^{N} \frac{(i-m)(j-m)P[i.j]}{s^{2}}$	Provides a correlation between the two pixels in the pixel pair. The Correlation is expected to be high if the gray-levels of the pixel pairs are highly correlated.
Maximum Probability (MP)	$\max_{i,j}^{M,N} P[i,j]$	Results in the pixel pair that is most predominant in the image. The MP is expected to be high if the occurrence of the most predominant pixel pair is high.
Inverse Difference Moment (IDM)	$\sum_{i}^{M}\sum_{j}^{N} \frac{P[i.j]}{\lvert i-j\rvert^{k}} \quad i \neq j$	Inverse Difference Moment tells us about the smoothness of the image, like homogeneity. The IDM is expected to be high if the gray levels of the pixel pairs are similar.
Cluster Tendency	$\sum_{i}^{M}\sum_{j}^{N} (i+j-2m)^{k} P[i,j]$	Measures the grouping of pixels that have similar gray-level values.