A Co-occurrence texture semi-invariance to direction, distance and patient size

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ABSTRACT

Texture-based models are intensively used in medical image processing to quantify the homogeneity and consistency of soft tissues across different patients. Several research studies have shown that the co-occurrence texture model and its Haralick descriptors can be successfully applied to capture the statistical properties of the soft tissues' patterns. Given that the calculation of the co-occurrence texture model is a computationally-intensive task, in this paper we investigate the usefulness of using all possible angles and all displacements for capturing the texture properties of an organ of interest, specifically, the liver. Based on the Analysis of Variance (ANOVA) technique and multiple pair-wise comparisons, we found that using only the "near" and "far" displacements is enough to capture the spatial properties of the texture for the liver.

Keywords: texture, segmentation, Computed Tomography

1. INTRODUCTION

Liver cancer is the fourth most common malignancy in the world. In particular, the hepatocellular carcinoma, the predominant liver cancer, accounts for approximately 6 percent of all cancer cases [1]. During the surgical preparation process, it is important to analyze the spatial information of the relative volume of the lesion compared to the overall liver. Automatic analysis of images from various medical imaging modalities is necessary to increase the productivity of radiologists when interpreting and diagnosing hundreds of images every day. Since soft tissues have overlapping gray-level ranges, texture properties can be used to quantify the homogeneity and consistency of soft tissues across multiple 2-D Computed Tomography (CT) slices. The most common texture models used in the medical field are co-occurrence matrices, Gabor filters, and Markov random fields [2,3].

There are several number of texture analysis techniques that have been used in image processing area. Generally, the texture study includes: structural, transform method, and statistical model[4]. The most common second-order statistic in medical field is co-occurrence texture models, which demonstrates better classification accuracy over the transform-based approach and structural method[5]. Co-occurrence matrix texture model have been intensively used to in texture analysis for identification of tissue to detect the abnormality within an organ tissue as well as an identification of different pathological grades in the context of both retrieval and classification systems [2,6]. Nonetheless, the co-occurrence matrices have been widely used in as a feature in registration and segmentation problems [7,8,9]. Based on our previous work on liver texture-based segmentation [10], co-occurrence texture model performs the best among these texture models. Therefore, in this paper we concentrate on the liver and the co-occurrence texture model, but the same experimental design can be applied to any other organ and texture model.

Furthermore, based on a literature review [5, 11,12,13], we found that the most common parameters were applied are distance length from 1, 2, 3 and 4 pixels with orientations of 0°, 45°, 90°, 135°. However, most of these research works calculate the co-occurrence matrix either across certain displacements and angles with no justification on the selection of the specific values of the two parameters.

The purpose of this paper is to present an experimental design whose output can help determine the best displacement-direction combo for liver's texture quantification through co-occurrence matrices in CT data.

2. METHODOLOGY

Contrast to the intensity, the texture is a surface property and it is a key component for human to perceive the region's properties such as randomness, coarseness, contrast, and smoothness. However, it is difficult for human observers to measure these texture qualities[13]. Therefore, a process of quantifying the texture patterns within the region is needed to analyze its texture properties. There are several texture models, including structural, transform methods, and statistical models [5]; among all of these models, it has been shown that the second-order statistical model (the co-occurrence matrix) produces better classification accuracy over the transform-based approach and structural method [14]. An overview of our proposed approach is shown in Figure 1.

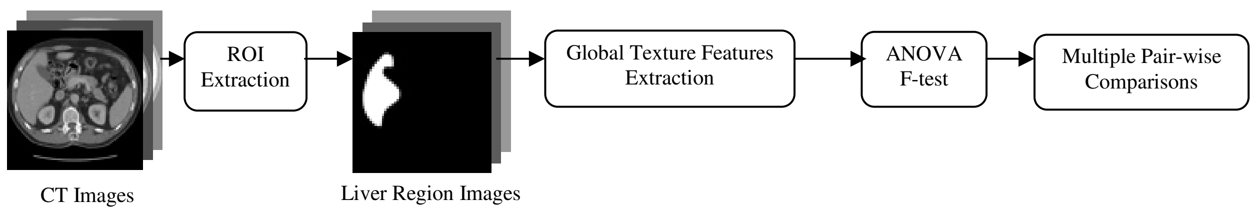

Figure 1: The diagram of the proposed approach

2.1. Global Texture Feature Extraction

Global texture extraction is the process of analyzing and quantifying the texture patterns within an entire region of interest.

As a statistical method for texture extraction, co-occurrence matrices focus on the distribution and the relationships among the gray levels in an image [15]. The general idea of a co-occurrence matrix is to represent an image's texture characteristics by counting pixel intensity pairs, using a matrix that keeps track of all the pixel-pair counts as shown in Figure 2 (b). The normalized co-occurrence matrix is denoted by $P_{ij}(d,\theta)$ where d is the displacement vector, θ *is* the an*gle*, and i and j represent the gray-levels in the vertical direction (along the rows) and horizontal direction (along the columns), respectively. In order to capture all possible texture patterns to be evaluated in a further step, we calculate four different displacements (1, 2, 4 and 8) for four directions (0°, 45°, 90°, 135°) as shown in Figure 2(a); Figure 2(b) shows example of the extraction of co-occurrence matrix within the corresponding region.

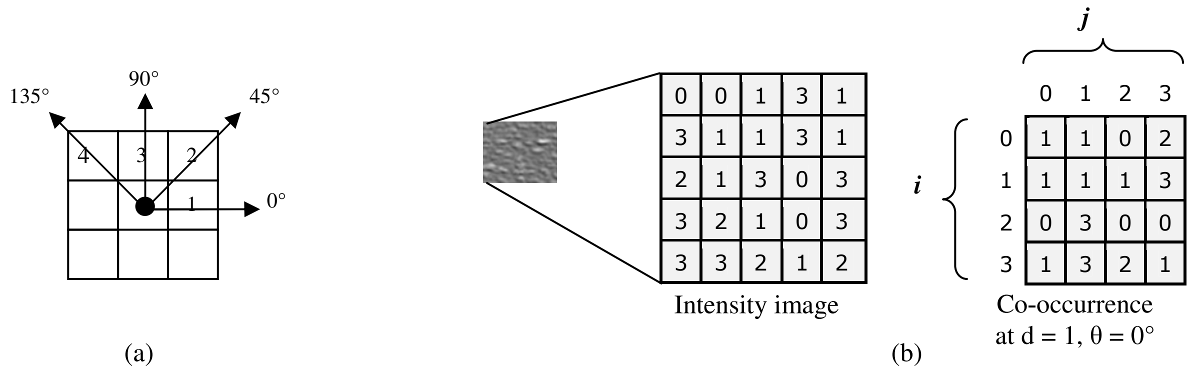

Figure 2: (a) From the centered pixel (•); pixel 1 represents *0°* at *d=1*; pixel 2 represents *45°*; pixel 3 represents 9*0°*and pixel 4 represents *135°*at *d=1*; (b) Co-occurrence matrix calculated at *d = 1, θ = 0° for a 5 by 5 neighborhood around the pixel of interest*

From the co-occurrence matrices, nine Haralick texture descriptors (Entropy, Energy, Contrast, Sum Average, Variance, Correlation, Maximum Probability, Inverse Difference Moment, and Cluster Tendency) are computed [16]. Brief definitions for each texture descriptor are provided in Table 1.

Table 1: Haralick texture descriptors used in the study

Haralick Texture	Description
Entropy	Measures the randomness of gray-level distribution.
Energy	Measures the occurrence of repeated pairs within an image.
Contrast	Measures the local contrast in an image.
Sum Average	Measures the average of the gray-level within an image
Variance	Measures the variation of gray level distribution.
Correlation	Measures a correlation of pixel pairs on gray-levels.
Maximum Probability (MP)	Determines the most predominant pixel pair in an image.
Inverse Difference Moment (IDM)	Measures the smoothness of an image
Cluster Tendency (CT)	Measures the grouping of pixels that have similar gray-level values

2.2. Evaluation Model

Analysis of Variance (ANOVA) is a statistical procedure[17] for determining the differences among means of two or more populations. ANOVA tests the null hypothesis of equal means for all populations, where the alternative hypothesis is the population means are not all equal. In multiple populations, there are two variances taken into account; 1) the variance within each of the samples and 2) the variance between the samples. An ANOVA F-test is applied in order to test the population means by examining the ratio of variation between the samples and the variation within the samples. If the F-test statistic is greater than the critical value, then the null hypothesis is rejected at the statistical level α. If it is less than the critical value, then we fail to reject the null hypothesis.

We perform Analysis of Invariance (ANOVA) on each one of the nine Haralick descriptors $d_{i,i=1...9}$ to see if their mean values μ_i are the same across displacements $disp_k, k = 1...l$:

$$\begin{aligned} &H_0 : \mu_{d_i, disp_1} = ... = \mu_{d_i, d_{ispl}} \\ &H_{a:} : at\_least\_one\_\mu_{d_i, disp_k}\_is\_different \end{aligned} \qquad (1)$$

If the null hypothesis H_0 is rejected and the alternative hypothesis H_a is accepted, it means that the corresponding descriptor is not invariant to distance and therefore, the distance calculation is important. Therefore, multiple pair-wise comparisons will be applied to further find the relationships among descriptors with respect to displacement.

A multiple-pair comparisons of Tukey-Kramer and Fisher's protected Least Significance Difference (LSD) tests[17] are performed to see if all distances are individually important or they can be grouped into different categories (such as "near" and "far" shown in Figure 3) so the numbers of co-occurrence matrices calculations could be significantly reduced.

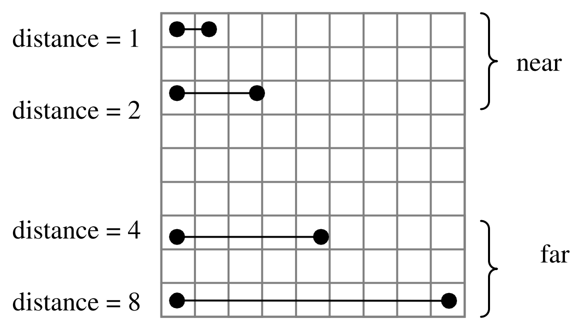

Figure 3: The distance "near" and "far" from the pixel of interest

We apply the same ANOVA model and the multiple pair-wise comparisons design to study the effect of $direction_{p,p=1...s}$ on the co-occurrence texture calculation in the case of the liver tissue as shown in (2). The hypothesis testing should lead us to a conclusion of invariance with respect to direction of the co-variance matrix with respect to the appropriate descriptor.

$$
\begin{aligned}
&H_0 : \mu_{d_i, direction_1} = \ldots = \mu_{d_i, d_{irection_s}} \\
&H_{a:} : at\_least\_one\_\mu_{d_i}, direction_s\_is\_different
\end{aligned}
\qquad (2)
$$

3. EXPERIMENTAL RESULTS

Our preliminary results are based on data extracted from normal CT images obtained from Northwestern Memorial Hospital (NMH) PACS. The data consists of multiple, serial, axial computed tomography images derived from helical, multi-detector CT abdominal and chest acquisitions using a HiSpeed CT/i scanner (GE Medical Systems). The images were transferred via Ethernet to a nearby computer workstation in DICOM format of size 512 by 512 and have 12-bit gray level resolution. The liver region of interest was manually marked by a radiologist from Northwestern Memorial Hospital. Figure 4 shows the gray level distribution of liver among five patients.

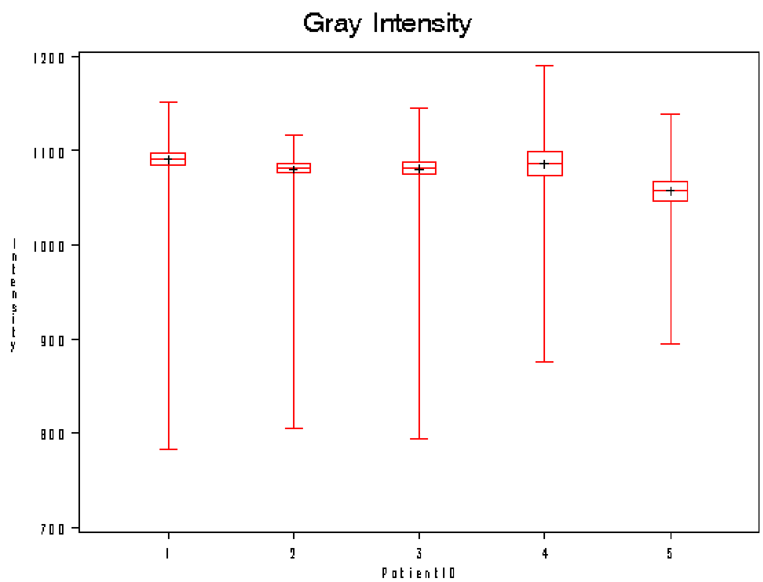

Figure 4: Side-by-side box plots showing the gray-level distribution for five patients

In order to calculate the texture model, the region of the liver has to be delineated; this is done manually by the radiologist. Then we calculated 16 co-occurrence matrices for each liver region corresponding to four directions (0°, 45°, 90°, 135°) and four displacements (1, 2, 4, and 8) as indicated in Figure 3. We chose the displacements up to a value equal to 9 based on our previous work[16] where we showed that the maximum window size needed to capture the texture information for soft tissues is equal to 9. In regards to direction, the four values chosen in this paper are the standard directions used in the co-occurrence literature.

Once the texture descriptors were calculated, the ANOVA tests (equations (1) and (2)) were performed to check the invariance with respect to the distances for each possible combination of type of descriptor and angle resulting in 36 tests. At a significance level of $\alpha = 0.05$ we found that at least one distance is different from all the others. Further, in order to see the differences in the texture descriptors with respect to distance, we performed pair-wise comparisons tests and we found that, regardless of the descriptor or angle, the first two distances (1 and 2) formed one group (named "near") and the last two distances (4 and 8) formed another group (named "far").

Similarly for direction invariance study, we performed 36 ANOVA tests and we found that there was not enough evidence to reject the null hypothesis that values of each texture descriptor is the same across directions. More patient data is needed to validate the invariance with respect to direction.

4. CONCLUSIONS

In this paper we present an ANOVA and multiple-comparisons design study to analyze the importance of the displacement and direction in encoding the texture information of the liver using the co-occurrence texture model and the Haralick texture descriptors. Based on our preliminary data with found that the first two displacements can be grouped group under the "near" category while the other two (4 and 8) can be grouped under the "far" category. The results are significant at a p-value of 0.05. Given the computational expensiveness of the co-occurrence model[16, 18], the results presented in this paper show that it is enough to encode the liver's texture information using only two displacements (e.g. 1 and 4) and therefore, reduce the calculations by half. As future work, we will continue to investigate the invariance with respect to direction and also with respect to other organs.

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