TEXTURE CLASSIFICATION AND SEGMENTATION USING SIMULTANEOUS AUTOREGRESSIVE RANDOM MODEL

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Abstract
In this paper, we use SAR model to describe texture. We also propose using the least-square method to estimate its parameters. Based on SAR model and the parameter estimation method, experiments have been done to classify and segment images of various natural textures and human B-Scan images. Excellent results have been made.

Introduction
Texture is an important property characteristic of the image. Many texture describing methods, e.g. SGLD and texture features have been proposed. Among all these methods, SAR model is one of the important. Texture features derived from SAR model possess strong discriminating power for texture. The main problem affecting the application of SAR model to image classification and segmentation is parameter estimation method. Usual methods such as ML estimation require so extensive computation that they are in fact impracticable. In this paper, we present the least-square method to solve the problem and have got good results.

SAR Model And Parameter Estimation Method
SAR Model
SAR model is a kind of two dimensional noncausal random field models called "Simultaneous Autoregressive". SAR model can be efficiently used to describe texture [1].
Suppose that \(g(x,y)|x,y=0,1,\ldots,M-1\) is a two dimensional matrix which represents a \(M\times M\) discrete image. If the SAR model applies to the image, then gray level \(g(x,y)\) and its neighborhood pixels satisfy:

\[
g(x,y) - \mu = \sum_{(i,j) \in N} \theta(i,j)[g(x \oplus i, y \oplus j) - \mu] + \sqrt{\mu} \omega(x,y),
\]

where:
- \(N\) denotes a spatial neighborhood set
- \(\mu\) is the mean of the gray levels
- \(\theta(i,j)\) a model factor indicating the correlation between a pixel and its neighborhood
- \(\oplus\) denotes the (Module M)
Parameter Estimation

The SAR models used in our experiment are defined on \( N_1 = \{(1,0), (0,1), (-1,0), (0,-1)\} \) and \( N_2 = \{(1,1), (-1,1), (-1,-1), (1,-1)\} \). By estimating \( (\theta(0,1), \theta(1,0), \rho) \) capturing the horizontal and vertical information of the texture from \( N_1 \) and \( (\theta(1,1), \theta(-1,1), \rho) \) capturing the information in the diagonal direction from \( N_2 \), we obtain 6 parameters which can be used as texture features. In this experiment, we design the least-square estimation that can be defined as follows:

\[
\begin{align*}
\theta &= \left[ \sum_{x=0}^{L-1} \sum_{y=0}^{L-1} Z(x,y)Z^*(x,y) \right]^{-1} \cdot \sum_{x=0}^{L-1} \sum_{y=0}^{L-1} Z(x,y)g(x,y) \\
\rho &= \frac{1}{L^2} \sum_{x=0}^{L-1} \sum_{y=0}^{L-1} [g(x,y) - \theta Z(x,y)]^2 \\
\theta &= \text{col}(\theta(i,j); (i,j) \in N_1) \\
Z(x,y) &= \text{col}[g(x \oplus i, y \oplus j); (i,j) \in N_2]
\end{align*}
\]

Using SAR Model To Classify Texture Images

We have made two classification experiments. In the first one, we select 4 images with different natural textures. They are the images of cowhide, sand, lawn, palmleaf respectively. In this process, each of the images offers 16 small sample window forming a training set with only one left out as the sample to be examined. The process is repeated 64 times in order that each small sample can be tested. The result of the training — testing performance is wonderful with the correct classification probability reaching 98%. The statistics of the 16 \( \times \) 4 samples are shown in table 1. In the second experiment, we select the B—Scan image of a patient’s liver as our sample. The liver has diseased areas. The performance of the classification is also very good with correct classification probability reaching 88%. The statistics are shown in table 2.

Using SAR Model To Segment Texture Images.

In this experiment, we use 6 SAR model parameters as texture features to segment two images. The first image consists of 6 areas with different textures, while the second is B—Scan image which contains both normal and diseased areas. In the segmentation process, the image is scanned from top to bottom in a row by row manner by a \( L \times L \) window. The window slides over the image in \( d \) —pixel wide steps in both horizontal and vertical directions overlapping each other in order to smooth out the transition from one texture region to the other. To each of these windows, we apply SAR model to extract a feature vector. The edges of different regions then can be detected in the places where texture features vary dramatically. As regard to the first image, as all the texture units are of the similar size, we select \( L=6, D=4 \). As to the second one, the win-
dow size is increased from 8 to 12 and the process is repeated in order to obtain the best segmentation result. The experiment results are shown in Fig 1 and Fig 2. In Fig 1 and Fig 2, a), b), c) are respectively the original image, the texture edge detected in a) and the overlap image of a) & b).

### Table 1. The statistics of four kinds of nature texture features

<table>
<thead>
<tr>
<th>kind of texture features</th>
<th>cowtide</th>
<th>sand</th>
<th>lawn</th>
<th>palmelnd</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(-1,1)$ mean</td>
<td>0.24962</td>
<td>0.23127</td>
<td>0.20436</td>
<td>0.17378</td>
</tr>
<tr>
<td>variance v/m(%)</td>
<td>0.00360</td>
<td>0.00483</td>
<td>0.00938</td>
<td>0.06581</td>
</tr>
</tbody>
</table>

| $E(1,0)$ mean          | 0.20502 | 0.24107 | 0.18233 | 0.21156 |
| variance v/m(%)         | 0.00620 | 0.00910 | 0.07164 | 0.02504 |

| $E(0,1)$ mean          | 0.12189 | 0.08547 | 0.6615 | 0.56716 |
| variance v/m(%)         | 0.00466 | 0.00290 | 0.14430 | 0.06581 |

| $E(-1,1)$ mean          | 0.211690 | 0.14903 | 0.88473 | 0.70835 |
| variance v/m(%)         | 0.01650 | 0.00848 | 0.04134 | 0.06581 |

### Table 2. The statistics of B—scan ultrasound image.

<table>
<thead>
<tr>
<th>area parameters</th>
<th>normal area</th>
<th>diseased area</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(0,1)$ mean</td>
<td>0.14423±0.04283</td>
<td>0.29654±0.03839</td>
</tr>
<tr>
<td>variance v/m(%)</td>
<td>0.00516±0.00478</td>
<td>0.09729±0.00591</td>
</tr>
</tbody>
</table>

| $E(1,0)$ mean   | 0.15326±0.04611 | 0.24462±0.05256 |
| variance v/m(%) | 0.00276±0.00235 | 0.04623±0.00743 |

| $E(-1,1)$ mean | 0.73548±0.14573 | 0.36623±0.17473 |
| variance v/m(%) | 0.00659±0.05275 | 0.06230±0.04030 |

| $E(-1,1)$ mean | 0.07998±0.03581 | 0.17913±0.06911 |
| variance v/m(%) | 0.00307±0.00874 | 0.04219±0.19196 |
Figure 1.
1. (a) original image containing 6 different textures.
1. (b) texture edge detected in 1. (a)
1. (c) overlap of (a) & (b)

Figure 2.
2. (a) B-Scan image of a liver.
2. (b) texture edge detected in 2. (a)
2. (c) overlap of (a) & (b)

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References