Texture classification and retrieval through space-frequency histograms

Salvador Gabarda
What is the meaning of texture classification and retrieval?

- **Classification** is a process for determining texture similarity, according to some visual content (features), normally associated to a training step.
- **Retrieval** is a process for searching through an image dataset, in order to determine the identity of the query image by a similarity measure.

This method has been designed to deal with image texture classification and retrieval, based on local-directional-space-frequency histograms (LDSFH).
Elements of the classification process through local-directional-space-frequency histograms (LDSFH)

- **Classification process**

- **Operations:**
  1. bark
  2. brick
  3. bubbles
  4. grass
  5. leather
  6. ........
Elements of the retrieval process through local-directional-space-frequency-frequency histograms (LDSFH)

- **Retrieval process**
- **Operations:**
  1. brick
  2. brick
  3. bubbles
  4. bubbles
  5. grass
  6. ..........
Orientation and fragmentation as occasional difficulties for pattern recognition

- **Other considerations**
  - Shards or fragments may show distinctive patterns in different orientations
  - Fragmented samples reproduce the statistics of the whole object, but differences may be greater when fragments become smaller

- **Requirements**
  - General behavior of the pattern
  - Local behavior of the pattern
  - Orientation of the pattern
  - Fragmentation of the pattern
Why a learning process is required?
Are ordinary histograms a good feature for texture recognition?

**Motivation**
- Textures can be associated to distinctive patterns
- Classification of patterns leads to identification and retrieval of textures

- Geometric patterns are mathematically exact
- Ordinary patterns are mathematically inexact

Histograms may be used to reveal the **general** behavior of gray-pixel values in images.

Histograms do not reveal information about **local** inexact behavior or pattern **directionality**.

**Local-directional-Space-frequency histograms** are proposed as an step-forward for texture classification and retrieval.
The von Mises distribution as key for frequency histograms orientation

Local-directional pseudo-Wigner distribution

Texture orientation

1) 

The von Mises distribution as key for frequency histograms orientation

2) 

This method uses the von Mises directional distribution of the Rényi entropy of the image to determine the direction $\mu$ of the texture with a maximum of entropy.
The pseudo-Wigner distribution as local support for histograms of image information

4) PWD is calculated in direction $\mu$, having $K=N$ discrete frequency values

$$W(n, k) = 2 \sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} z(n + m)z^*(n - m)e^{-i2\pi k\left(\frac{2m}{N}\right)}$$

Histograms are calculated and stored as a feature
Similarity measure for histograms

**Similarity**

The similarity measure of the histograms is based on the Sørensen-Dice coefficient

\[ S = \frac{2|H_1 \cap H_2|}{|H_1| + |H_2|} \]  

\(|\cdot|\) is interpreted as a summ

\(H_1 \cap H_2\) is interpreted in each bin as the minimum reading in \(H_1\) and \(H_2\)

\(|H_1| + |H_1|\) is the total number of readings
Building a model-histogram by supervised error correction

**Learning process**

Reference set:
\[ H = \{H_1, H_2, H_3, \ldots, H_n\} \]

Query set:
\[ Q = \{Q_1, Q_2, Q_3, \ldots, Q_m\} \]

Query histogram \( Q \)

Histogram \( H \) updating

Histogram \( H \) vs Query \( Q_j \)

Similarity measure

Error \( e \)

\[ H_j - f(e) \]

Accurate identification:
\( H \) does not change
Experimental examples

- Experimental data taken from Brodatz, Outex and VisTex texture images
- Orientation and fragmentation are the key characteristics to be considered

Example of texture from SIPI Database
Category: brick


Performances of the LDSFH method

**Experimental data I**

*Original set:* 91 Brodatz images distributed in 13 categories with 7 different orientations, 512x512 pixels

<table>
<thead>
<tr>
<th>texture database</th>
<th>number of images</th>
<th>size (pixels)</th>
<th>number of scales</th>
<th>learning step</th>
<th>right matches</th>
<th>wrong matches</th>
<th>retrieval accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brodatz</td>
<td>91</td>
<td>512 x 512</td>
<td>4</td>
<td>no</td>
<td>90</td>
<td>1</td>
<td>98.9</td>
</tr>
<tr>
<td>Brodatz</td>
<td>91</td>
<td>512 x 512</td>
<td>3</td>
<td>no</td>
<td>90</td>
<td>1</td>
<td>98.9</td>
</tr>
<tr>
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<td>91</td>
<td>512 x 512</td>
<td>2</td>
<td>no</td>
<td>85</td>
<td>6</td>
<td>93.4</td>
</tr>
<tr>
<td>Brodatz</td>
<td>91</td>
<td>512 x 512</td>
<td>1</td>
<td>no</td>
<td>72</td>
<td>19</td>
<td>79.1</td>
</tr>
</tbody>
</table>

| Table 2: Retrieval results for randomly sub-sampled SIPI images, after application of LDSFH method + learning

<table>
<thead>
<tr>
<th>texture database</th>
<th>num. imag. in test set</th>
<th>num. imag. in learning set</th>
<th>size (pixels)</th>
<th>right matches</th>
<th>wrong matches</th>
<th>retrieval accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brodatz</td>
<td>910</td>
<td>455</td>
<td>256 x 256</td>
<td>440</td>
<td>15</td>
<td>96.7</td>
</tr>
<tr>
<td>Brodatz</td>
<td>910</td>
<td>455</td>
<td>128 x 128</td>
<td>378</td>
<td>77</td>
<td>83.1</td>
</tr>
<tr>
<td>Brodatz</td>
<td>910</td>
<td>455</td>
<td>64 x 64</td>
<td>301</td>
<td>154</td>
<td>66.2</td>
</tr>
<tr>
<td>Brodatz</td>
<td>910</td>
<td>455</td>
<td>32 x 32</td>
<td>227</td>
<td>228</td>
<td>49.9</td>
</tr>
</tbody>
</table>
5% of the categories accumulate the 80% of the errors then: a second feature have to be used to solve discrimination

**Experimental data II**

Original set: 261 Outex images, distributed in 29 categories with 9 different orientations, 538x746 pixels

**Figure 5:** Distribution of errors in a retrieval operation with the LDSFH method with a sample of 75 images of $538 \times 746$ pixels, from Outex image database, after a learning process over 186 non-overlapping rotated images. Note how the 5% of the categories accumulate the 80% of the errors.
Table 4: Retrieval results for randomly sub-sampled VisTex images, after application of LDSFH method + learning

<table>
<thead>
<tr>
<th>texture database</th>
<th>num. imag. in test set</th>
<th>num. imag. in learning set</th>
<th>size (pixels)</th>
<th>right matches</th>
<th>wrong matches</th>
<th>retrieval accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VisTex</td>
<td>500</td>
<td>1000</td>
<td>256 × 256</td>
<td>447</td>
<td>53</td>
<td>89.4</td>
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<tr>
<td>VisTex</td>
<td>500</td>
<td>1000</td>
<td>128 × 128</td>
<td>408</td>
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<td>81.6</td>
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<tr>
<td>VisTex</td>
<td>500</td>
<td>1000</td>
<td>64 × 64</td>
<td>328</td>
<td>172</td>
<td>65.6</td>
</tr>
<tr>
<td>VisTex</td>
<td>500</td>
<td>1000</td>
<td>32 × 32</td>
<td>265</td>
<td>235</td>
<td>53.0</td>
</tr>
</tbody>
</table>

Figure 6: Distribution of errors in a retrieval operation with the LDSFH method with a sample of 500 images of 256 × 256 pixels, cropped from 20 non-rotated original images of VisTex image database with a random amount of overlapping. A learning process over another 1000 similarly generated images have been performed for training the model histograms. Note how the 1.5% of the categories accumulate the 72% of the errors
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Conclusions
- Classification and retrieval of textures is possible with the help of the LDSFH method
- Discrimination becomes more difficult as texture samples are getting smaller
- The great amount of histogram coincidence in smaller texture samples will require the use of additional features

Future work
- Add new discriminating features to the process
- Experiment with another learning methods as Support Vector Machines (SVM) or Artificial Neural Networks (ANN)
- Study new solutions to solve histogram coincidence between conflictive categories
- Compare results with other methods under a normalized framework
Thanks for your attention