Perceptive Visual Texture Classification and Retrieval

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Abstract

In this paper we present some analysis techniques and indexing strategies aimed to support classification and retrieval of textures using only perceptual features. The goal of this research is to provide a visual system that starting from graphical cues representing relevant perceptual features of texture, interactively searches the most similar texture in the set of candidates in the correspondent texture space.

A set of perceptual relevant features, used for indexing is hence proposed: directionality, contrast and coarseness. A graphical representation of the computed characteristics is presented together with some examples. Finally experiments of texture retrieval using such iconic representation are presented and discussed.

1. Introduction

Textures have attracted considerable attention both from the Computer Vision community and the Computer Graphics community. Indeed to understand the processes behind the human perception of an image as a "pattern" or a "texture" involves deep questions about human brain organizations that are relevant for those that try to simulate the human vision mechanism.

The first and oldest approach to texture classification is based on statistics. Textures are described using mathematical models and a set of purely statistics features of a texture can be computed in order to achieve both supervised and unsupervised classification [6][7][11][26].

The alternative approach to texture classification tries to identify and measure features that are considered relevant for human perception. We propose some computational definition of the confidence level of some perceptual features, directionality, contrast, coarseness, based on local properties. These features have been used to produce a multidimensional "perceptual space" in which textures are organized depending on perceptive axes. The computed features may be adopted to create a visual system for the browsing and retrieval of texture in a large database. Following a Visual Data Mining approach [14][28] we would like to translate "hard" numbers into visual information by the way of an iconic representation. These representations are used in turn to formulate interactive visual queries to search textures with respect to perceptual qualities cues.

The rest of the paper is structured as follows. Section 2 describes the perceptual texture features used for indexing and provides technical details of the measures chosen for their computation. The next Section is devoted to the description of the iconic representation. A suitable "glyph" is then proposed and directly used in the visual query system as described in Section 4. The overall system has been validated by an exhaustive experimental phase as reported in Section 5. A final section closes the paper tracking directions for future researches.

2. Perceptual Indices

The description of texture by perceptual relevant features has involved many researchers both in computer vision and visual perception. The seminal work in this research line is due to Tamura et alii [25] that described and provided computational measures for six perceptual features validating their proposal with subjective experiments.

From psychological point of view, a fundamental work that tried to identify high level features in texture perception is due to Rao et alii [24]. Basing on their subjective experiments, they proposed a triple of discriminating features (directionality, periodicity and complexity). They underlined also the importance of choosing orthogonal features in order to design a suitable texture space.

More recently Long and Leow [18][19] presented a framework to improve image retrieval performance using neural networks trained with information obtained by subjective experiments.

Perceptual indices have been largely used both in texture retrieval and content-based image retrieval (CBIR) systems [8] like:

- *IBM QBIC* system [9] which implements Tamura features;
- *Candid* by the Los Alamos National Lab's by Kelly et alii [15] using Laws filters [16];

- *Photobook* [23] by Pentland et alii from MIT referring to Wold Texture decomposition model [17];
- *Netra* [20], introduced by Manjunath et alii [21] using Gabor filters and perceptual browsing component.

In the rest of this section three perceptual features, directionality, contrast and coarseness, will be described and computationally defined. These three indices represent a “semantic-sign” used to discriminate textures in a database in a coherent way to the human vision system.

2.1. Directionality

Our measure of directionality is based on co-occurrence matrices, first introduced by Haralick [10].

Differently than [1][22][25] where the preferred direction (vs. isotropy) is derived analyzing the distribution of the angles through the gradient values, we focused on the computation of the confidence degree for a given orientation of the texture. In other words instead of computing a global value of “directionality”, we provide a “degree of confidence of relevance” for a set of orientations.

Let T a texture of size $n \times m \times c$ colors and $v=(x,y)$ an offset vector, the co-occurrence matrix $C(T,v)$ is a $c \times c$ matrix defined in each point by:

$$C(T,v)_{i,j} = |\{ (p,q) \text{ in } T \times T : q = p + v \text{ and } L(p) = i \text{ and } L(q) = j\}|; \quad (1)$$

where $L(p)$ is the luminance value of the pixel p.

Then a point (i,j) in C contains the number of pixels pairs in T that have respectively gray level i and j and with displacement vector v.

Co-occurrences matrices collect second-order statistics of a texture that, according to Julesz’s conjecture [13], are used for discrimination; they have been largely used also for classification and retrieval trough a set of well known measures [10].

The proposed measure is based on a simple idea: the plot of the main diagonal of a co-occurrence matrix with offset v is as closer to the histogram of the image as v is relative to a relevant direction.

In Figure 1 is shown the plot of the histogram relative to a texture, together with the plot of the main diagonal of the co-occurrence matrix relative to the *(1,1)* offset and the plot of the main diagonal of the co-occurrence matrix relative to the *(-2,-2)*. The three plots clearly suggest that the relevance of a direction is inversely related with the discrepancy of its plot with respect to the histogram.

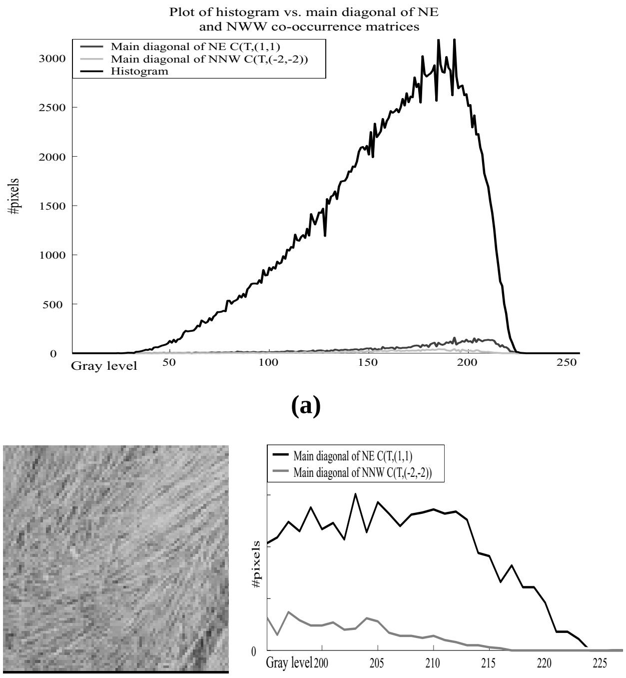
Starting from this observation we suggest to quantitatively estimate the relevance of a direction computing how much the diagonal of the co-occurrence matrix relative to such a direction deviates from the histogram of the image.

More precisely, given a co-occurrence matrix $C(T,v)$, let $d_C(t) = C(T,v)_{t,t}$, $t = 0\ldots c$ and $H(t)$ the histogram of T. We propose to compute the area between the plot of the histogram and d_C as a measure of the deviation of the co-occurrence matrix with respect to the histogram.

The discrepancy of matrix C is defined by the expression:

$$d(C) = \sum_{t=2}^{c-1} \left(H(t) - d_C(t) \right) + \frac{1}{2} \times \left(H(1) - d_C(1) + H(c) - d_C(c) \right) \quad (2)$$

The expression above is similar to trapezium method formulae for the numerical integration.



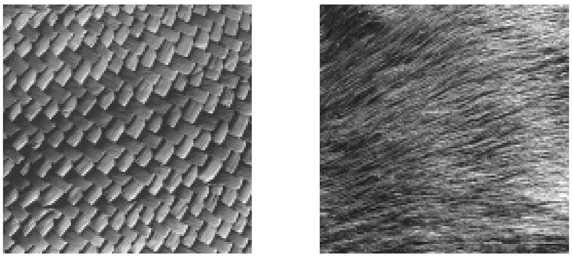
(a)

(b) (c)

Figure 1. **(a) Plot of the histogram of the texture in and main diagonals of C(T,(1,1)) and of C(T,(-2,-2); (b) A texture from Brodatz database; (c) Zoom of the lower right corner.**

Alternatively the co-occurrences matrices are often described in literature to emphasize the distance from pixel and direction. This representation uses distance (radius) d and angle θ instead of vector v. In this notation for example $C(T,v(1,0))$ becomes $C(T, d=1, \theta = 0)$. The advantage of this representation lies on the immediate interpretation of the spatial relationship of pixel in the co-occurrence matrix. Thus, in order to observe the behavior of the directionality of the texture, the discrepancy values must be computed for a set S of vectors with increasing distance $d=1, 2, \ldots, D$.

To obtain the relevance of a direction from the discrepancy measure defined above over a finite family S of offsets we suggest the following: let D_S be the matrix of the discrepancy values of the co-occurrence matrices relative to the offsets in S and d_S be the set of the normalized values (levels $d=1, 2, \ldots, D$) of D_S in $[0,1]$.
We claim that the set $R_S = 1 - d_s$ provides a set of relevance measure of the directions in the family S for the texture under examination. See [2] for further details.
Figure 2 shows the 2 textures in the Vis Tex database [27] on which the proposed measure with respect to the right diagonal direction gives the two extrema values.



Fabric.0002 Fabric.0006

Figure 2. **The less and the most directional (as respect to the right diagonal direction) texture in the Vis Tex databases.**

2.2. Contrast

Local contrast is commonly defined for each pixel as an estimate of the local variation in a neighborhood. More precisely, given a pixel $p=(i,j)$ and neighbor mask $W \times W$ of the pixel, local contrast is computed as:

$$local\_contrast(i, j) = \frac{\max_{p \in W \times W}(p) - \min_{p \in W \times W}(p)}{\max_{p \in W \times W}(p) + \min_{p \in W \times W}(p)} \quad (3)$$

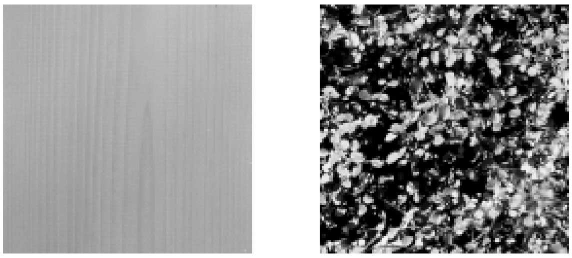
We propose to measure the global contrast as the global arithmetic mean of all the local contrast values over the image:

$$contrast = \frac{1}{m * n} * \sum_{i=1}^{n} \sum_{j=1}^{m} local\_contrast(i, j) \quad (4)$$

where n, m are the dimensions of the image.

In Figure 3 are shown the most and the less contrasted textures in Vis Tex texture database [27] as respect to the proposed measure with a neighborhood window of 7x7 size.

We have computed global contrast using different windows sizes (3x3, 5x5, …). As the window size changes the contrast measure changes of a small factor that is approximately the same for all the images in our test databases. For this reason we decided to take into account windows of fixed size (i.e. 7x7).



Wood.0002 Leaves.0004

Contrast = 0.021580 Contrast = 0.797274

Figure 3. **The less and the most contrasted texture in the Vis Tex database.**

2.3. Coarseness

Coarseness is probably the most essential perceptual features, since in many cases the word "coarseness" is used instead of "texture". If two textures differ only in scale, then the magnified one is coarser [25].

According to a dictionary[1] definition coarseness is: "the quality of being composed of relatively large particles [syn: graininess, granularity]".

The computational definition used in this paper, derived from Rosenfeld [12], consists of the computation of the size of the structural element of texture using various sized operators.

Their method is a multi-step algorithm that is here briefly described:

Step 1: Build K images in which each element is the average of intensities in a neighboring $2^k \times 2^k$, $k=1, 2, \ldots, K$):

$$A_k(x, y) = \frac{1}{2^{2k}} * \sum_{i=x-2^{k-1}}^{x+2^{k-1}-1} \sum_{j=y-2^{k-1}}^{y+2^{k-1}-1} T(i, j) \quad (5)$$

Step 2: Take differences between pairs of average that correspond to non-overlapping neighborhood both in vertical and horizontal orientation.

$$E_{k,horizontal}(x,y) = | A_k(x+2^{k-1},y) - A_k(x-2^{k-1},y) | \quad (6)$$

$$E_{k,vertical}(x,y) = | A_k(x,y+2^{k-1}) - A_k(x,y-2^{k-1}) | \quad (7)$$

Step 3: For each point, compute the best size of the neighbor mask (that is the structural element) as the maximum difference among adjacent regions. $S_{best}(x,y)=2^k$ where k maximizes the differences: $E_k=max(E_{k,horizontal}, E_{k,vertical})$. In our experiments we prefer to take $S_{best}(x,y) = k$.

Step 4: Compute a global coarseness value as the average of the S_{best}:

$$coarseness = \frac{1}{n * m} \sum_{i=1}^{n} \sum_{j=1}^{m} S_{best}(i, j) \quad (8)$$

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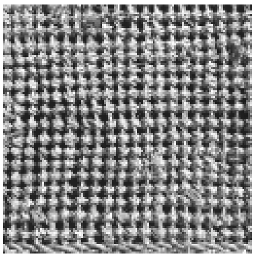
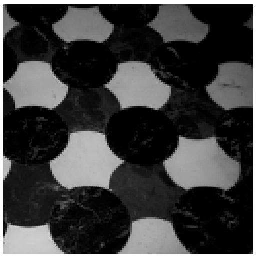
[1] WordNet ® 1.6, © 1997 Princeton University

In order to obtain a degree of coarseness, we normalized S_{best} values in the range [0,1]. The Figure 4, shows also in this case the Vis Tex textures corresponding to the two extrema values with respect to such measures.



Fabric.0009
Coarseness = 0.086690



Tile.0003
Coarseness = 0.910828

Figure 4 - **The coarsest and the finest texture in the Vis Tex database.**

3. Visual Queries

Using the proposed indexing a texture *T* is identified by the directionality matrix, the contrast and the coarseness measures. The first component is a matrix (for simplicity 5x5, i.e. relative to the set of offset vector with distance 2), the last two are scalars.

A visual data mining approach in texture retrieval uses some kind of visualization and user interaction to mine data. Since our approach in describing textures is related with perceptual relevant features, we would like to provide together with computational measures, a visual way to describe textures. Iconic representation seems to be the most feasible approach given the perceptual aspects of the features taken into account. From one side the system is able to visually describe a texture capturing the essential qualities (from a perceptual point of view) of the image. Figure 5 and Figure 6 show examples of textures with the corresponding glyphs. The "thickness" of the various lines is directly related to the perceptual weight associated to each preferred direction involved in the desired and/or retrieved texture, while the colour background of the glyph is proportional to the contrast value.

On the opposite side the iconic representation constitutes a tool for interactive browsing/querying the database of textures.

In general it is possible to interactively design a visual query able to capture the perceptual description of the texture to search for, i.e. query like "search all texture in the database that have these orientations and given contrast and coarseness". Notice that this description a query "by example", that is a search in the database starting from a specific sample.

The system has been intended to be easy to use tries to simulate the humans mechanism of texture selection.

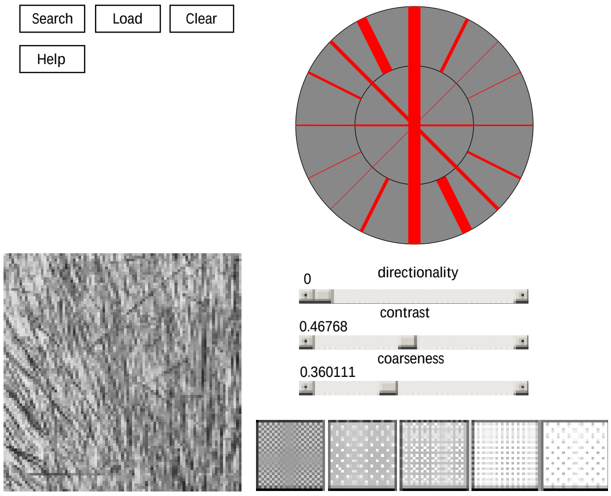


Figure 5 - **Visual description of texture d15 from Broadtz album [5].**

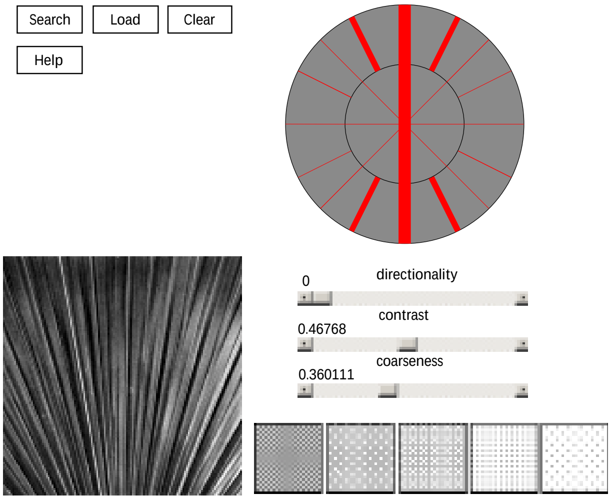


Figure 6. **Visual description of texture Wood.0002 from Vis Tek database [27]**

4. Perceptual Retrieval

Once the query has been formed, the search in the database may be performed using different metrics and selecting which features have to be considered.

All these parameters are chosen by the user selecting the search button. In our experiments we used two databases (Vis Tex and Brodatz) containing, for each record, the filename and the measured perceptual indices.

These values are properly normalized and scale-independent in order to work also with textures having different size or belonging to different databases.

In order to design a suitable metric for the comparisons we experimented with the Euclidean metric L_2 over the 27 components of the vector query, with a metric L_2w

weighting each one of the three perceptual features in the same way, and with metric L_{max}.

We considered the L_2w metric as the most suitable, although other metrics and data structures may be used in order to improve both accuracy and efficiency.

The mathematical expression of the L_2w weighted is:

$$dist(X,Y) = \left|c - c^*\right| + \left|r - r^*\right| + \frac{1}{25}\sqrt{\sum_{i=1}^{D}\sum_{j=1}^{D}\left(D_{i,j} - D^*_{i,j}\right)^2} \quad (9)$$

where:

- $X = (D,c,r)$ is the query;
- $Y = (D^*,c^*,r^*)$ is the database element;
- $D_{i,j}$ = Directionality matrix (size D x D);
- c is the contrast value;
- r is the coarseness value.

5. Experimental Results

All the features described in section 2 have been implemented (in C) and experimented on two standard database of textures: Vis Tex [27] and Brodatz [5], while the browsing-retrieval system, named Visualization Toolkit – Texture (VisTo-Tex), has been implemented in Matlab.

The first experiment regards the performance of the system with queries "by example". Figure 7 shows an example of execution, where the six images retrieved, including the query itself (distance = 0), are depicted with distance values and filenames.

Another experiment has been performed to show the effectiveness of the system with query drawn with user interaction. The results of the query, designed for searching textures with a horizontal direction, low contrast (0.2) and medium coarseness (0.4), respectively with metric L_2w and L_2 are shown in Figure 8 and Figure 9.

Finally, in order to test the overall system with respect to the perceptive texture features, we used a subjective experiment involving 10 people. First, we have randomly selected 10 different textures from Vis Tex database to be used as query-by-example (see Figure 10). For each selected texture to each people been asked to select the 4 most similar textures, from a perceptual point of view. The 10 input texture have been also used in our VisTo-Tex system retrieving also in this case the best 4 results. We have then compared the overall results coming from the subjective experiments with the automatic retrieval. The results showed an average performance of correctness of 52%., i.e. on the average, two of the four textures selected by the majority of the humans have been also taken by the system.

More experiments and details can be found at the following web-site: *http://alpha.dmi.unict.it/~vistotex*.

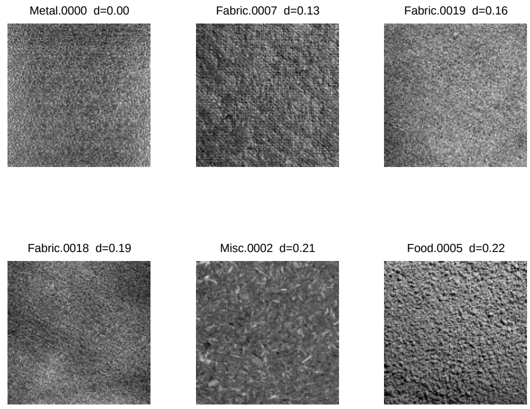


Figure 7. **Results of query "by example".**

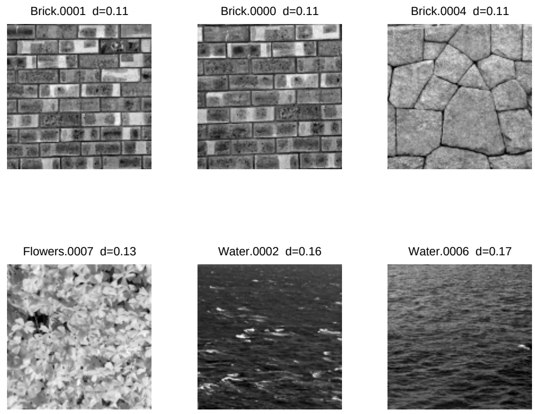


Figure 8: **Results of a visual query (horizontal direction, low contrast and medium coarseness) with metric L_2w.**

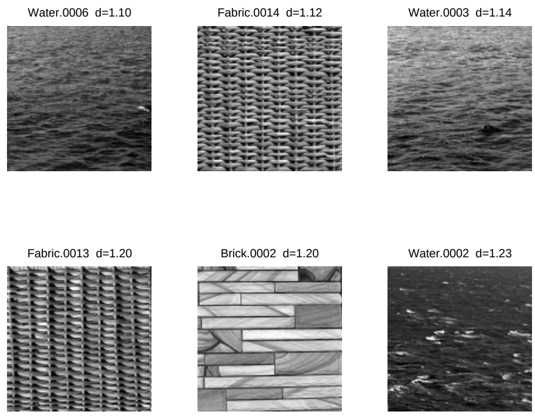


Figure 9: **Results of the same visual query described in Figure 8 with metric L_2.**

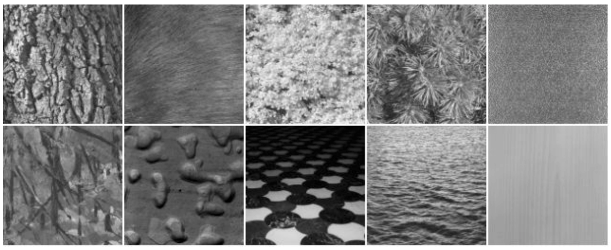


Figure 10: **Ten images, randomly chosen from Vis Tex database, used for subjective experiments.**

6. Conclusions and Future Works

A suitable indexing scheme based on perceptual texture features has been proposed. The system uses some perceptual features such as directionality, contrast and coarseness to build, by using an iconic representation, a perceptual texture retrieval framework. Experiments over classical texture database assess the effectiveness of the overall system proposed.

Future works will include the possibility to enrich the iconic representation with further perceptual features.

Also advanced indexing/retrieval methods will be exploited. The retrieval texture system will be also integrated with a synthesis engine [3][4].

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