GLYPH REPRESENTATION OF DIRECTIONAL TEXTURE PROPERTIES

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ABSTRACT

A novel approach to visually represent perceptual features of textures is proposed and analysed. This approach combines statistical properties of the texture together with qualitative measures coming from human perception. Quantitative measures, coming from co-occurrence analysis, have been in turn visually represented using an effective iconic representation, producing an immediate and easy tool to discriminate a texture from a larger set. Such a representation is very effective to formulate approximate queries to a database of textures for similarity based retrieval.

Keywords: Texture perception, iconic representation, scientific visualization.

1. INTRODUCTION

Texture perception is one of the leading problems of computer vision. To understand which visual properties of a texture are more relevant for human perception is not only a relevant scientific question, but it is also an interesting cue for computer graphics and scientific visualization. Once a suitable "texture space" has been parameterised using few perceptual relevant features it is indeed possible to represent complex multivariate phenomena using texture [Inter00a]. Vice versa it may be of practical relevance to ask a user to "design" the texture that he needs for his application and to retrieve from a large database those textures that are perceptually more similar to his query.

Tuceryan and Jain [Tucer93a] classify textures models into statistical methods, geometrical methods, model-based methods and signal processing methods.

As for the point of view that we take in this paper, there are, in literature, two major trends in classifying texture.

The first and oldest approach to texture classification is based on statistics (see for example chapter 17 in [Pratt91a] or the seminal work of Haralick [Haral79a] or [Cross83a, Weska76, Winkl95a]).

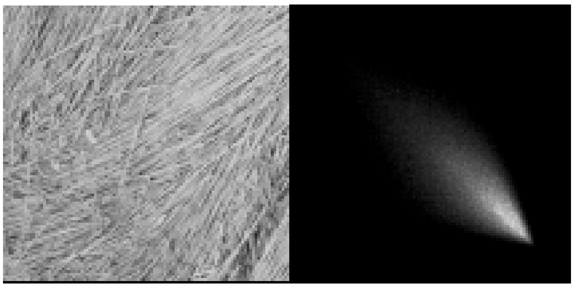
Although this technique is very powerful to discriminate one texture from another, there is, at today, no clear understanding on how statistical properties relate with human perception (see for example the intriguing discussion about these issues in [Jules96a]). This approach is valuable for computer graphics because it naturally leads to models and algorithms to synthesise new texture starting from samples [Burt83a, DeBon97a, Efros99a, Heege95a, Ogden85a, Perlin89a, Simon92a ,Wey00a ,Zhu98a, Zhu00a].

The alternative approach to texture classification tries to identify and measure features that are considered relevant for human perception. This kind of researches dates back to the ideas of [Tamur78a]. A nice summary about this approach can be found in [Rao93a].

The features used in different studies include:

- periodicity vs. non periodicity
- directionality vs. non directionality
- coarse vs. fine
- deterministic vs. random
- spatially invariant vs. heterogeneous
- high contrast vs. low contrast.

The power of this approach lies on the immediate semantic value of the features that are taken into account. On the other hand it is hard to device quantitative methods to support this kind of



(a) **(b)**

Fig. 1 *Texture T (a) and grey level representation of C(T,(-1,0)) (b).*

classification that are robust relatively to noise, perspective deformation and scale.

There is a clear need to build a bridge between the two approaches: translate the vagueness of human texture perception into "hard numbers" and vice versa to better understand the role of the statistical proprieties of a texture in creating a visual sensation.

Any insight into this issue is also potentially very relevant to retrieve images from large databases.

This paper inscribes itself into the proposals to build such a bridge. In particular we propose a visualization technique that translates the hard numbers coming from co-occurrence analysis into graphical information that can be used by a human observer to discriminate between different textures.

In this paper, for sake of demonstration, we present a simple, but very relevant texture feature: directionality, i.e. the presence of preferred directions in the image.

However, preliminary experiments on other perceptual features (contrast, randomness) are giving encouraging results.

In the following, we first suggest a simple technique that uses co-occurrence matrix to provide a quantitative measure of the relevance of a direction, at a given scale, for a pattern. Although the technique is very intuitive we have found no references to it in the literature.

The technique provides as with an array of "relevance measures" that may be quite inexpressive not only to the layman but also to a trained computer graphics expert.

For this reason we complement such measure with an iconic representation. In particular we propose a circular glyph that naturally maps the relevance of a direction with line thickness.

To prove the soundness of our proposal we have implemented a complete interactive system to analyse and represent direction relevance of grey level textures.

We have tested our approach over a large subset of Brodatz texture collection [Broda66a].

The experiments performed to validate our approach show its full validity and effectiveness as it reported later in the paper.

The structure of the paper is the following:

In section 2 the co-occurrences matrices are introduced together with the proposed directionality measure. The next section introduces the related iconic representation while in section 3 experiments showing real effectiveness of the method are reported. Finally, conclusion section ends the paper addressing future related work.

2. CO-OCCURRENCE MATRICES AND DIRECTIONALITY MEASURE

In this section we first report the definition of co-occurrence matrix for a texture and consider a simple example to provide motivations for our proposal of a quantitative measure for direction relevance.

Let

- T be a 256 grey level image of size $n \times m$ pixels;
- $L(p)$ the luminance level of pixel p of T;
- **v** = (x,y) be an offset vector;

The co-occurrence matrix ***C****(T,v)* is the 256 x 256 array of integers defined as follows:

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

In other words **C** collects the second order statistics of texture **T**. When no ambiguity can arise we adopt a sloppier notation and write **C** instead of **C(T,v)**.

It is well known that **C** is very important for the perceptual properties of a texture, although the long standing conjecture of Julesz [Jules96a, Berge93a] that **C** is *deterministically* linked to perceptual proprieties has been disproved [Pratt91a, Diaco81a].

The matrix **C** is very large and a human may hardly understand it simply reading the figures in it. For this reason it is customary to represent **C** as a grey level picture obtained with a suitable look up table. An example of texture and one of its related co-occurrence matrix is reported in figure 1.

This representation is not completely satisfactory because there is no natural mapping between the visual appearance of the texture and the visual appearance of **C**. Moreover for every different offset vector a new co-occurrence matrix should be observed and it becomes quickly meaningless to look at an array of such matrices. For example the complete set of co-occurrence matrices relative to the 24-neighbors offsets of the texture in figure 1a is reported in figure 2.

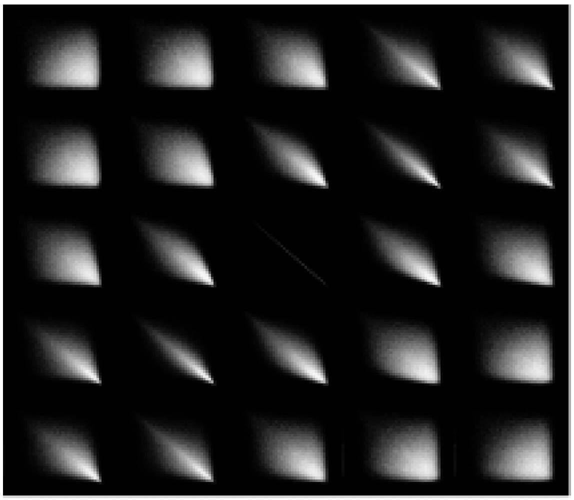


Fig. 2 *Visual Representation (normalized grey level) of the set S of co-occurrence their spatial order.*

As the reader may observe by herself figure 2 does not provide any useful insight about the properties of the texture. In particular it is unlikely that an observer would understand that the texture in figure 1a has a strong 45 degree directionality simply looking at figure 2.

To overcome such kind of problem in [Haral79] several statistical measures directly computed on ***C*** have been proposed while in [Gotli90a] an heuristic selection methods tries to select the best subset of features for ***C*** but in any case no general solution has been found yet.

In the rest of this paper we suggest a simple measure for the relevance of a direction in a texture. Such a measure is indeed derived from a set of co-occurrence matrices. In order to understand the idea behind our proposed directionality measure let us go back to fig. 2.

Since in the texture there have quite coherent 45 degree strips the co-occurrence matrix relative to a 45 degree offset appears less sparse than a co-occurrence matrix relative to any other kind of offset.

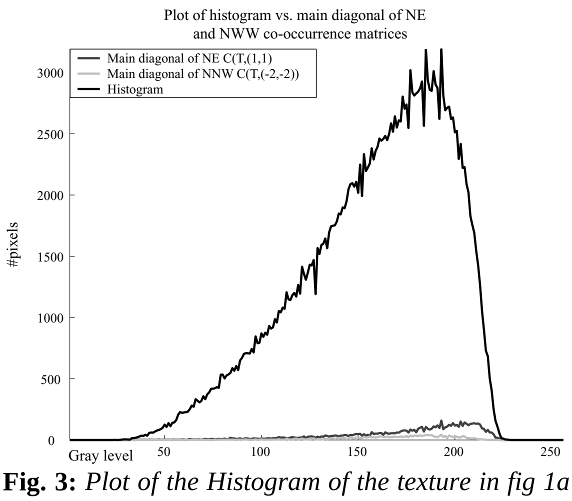


Fig. 3: *Plot of the Histogram of the texture in fig 1a and main diagonals of C(T,(1,1)) and of C(T,(-2,-2).*

Ideally if the only relevant direction in a texture is the diagonal one there should be no non-zero values off the main diagonal of a co-occurrence matrix. This for example is the case for a texture made of homogeneous diagonal strips. In this last case one could "read off" the image histogram simply looking at the main diagonal.

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.

In figure 3 the reader may see the plot of the histogram relative to the texture in figure 1a, 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.

More precisely, given a co-occurrence matrix **C**, let $d_C(t) = C(t,t),\ t=0,\dots,255$. Let $H(t)$ be the histogram of the image. We define the discrepancy of matrix **C** the expression:

$$
\begin{aligned}
discrepancy(C) = &\Sigma_{t=1}^{254} (H(t) - d_C(t)) + \\
&1/2*(H(0) - d_C(0)) + \\
&1/2*(H(255) - d_C(255))
\end{aligned}
$$

In order 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 $\mathbf{D}_S$ be the set of the discrepancy values of the co-occurrence matrices relative to the offsets in *S*. Let d_S be the set of the normalized values of $\mathbf{D}_S$ 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.

To clarify our proposal consider the worked example below relative the texture in fig. 1a. For this example the set *S* is the set $\{(i,j): i = -2\dots2, j = -2\dots2\}$.

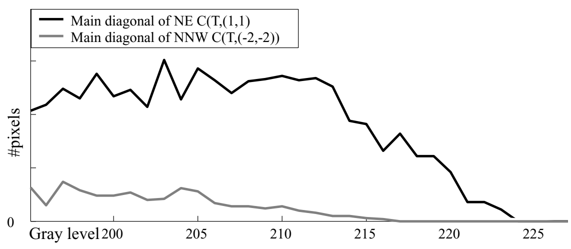


Fig. 4: *Zoom of the lower right corner on fig 3. Notice how the plot of the diagonal of a co-occurrence matrix relative to a preferred direction of a texture dominates the correspondent plot relative to a non-preferred direction.*

The discrepancy value set is reported in table 1. The discrepancy values have been arranged according to their spatial order. The normalized discrepancy value set is shown in table 2, while in table 3 the relevance coefficients set is given.

Because of the obvious intended meaning, in the rest of the paper we refer to the relevance coefficients as defined above also with the term directionality measure.

An alternative way to measure the amount of directionality in a texture uses gradient computation. In particular one may compute gradient at a given scale over the texture and quantize the range of the angles taken by the gradient into finite number of discrete bins. To plot the relative frequencies of these bins produces a visual way to evaluate direction relevance.

In this paper we have preferred the approach based on co-occurrence matrices because we believe that many other visual texture properties (contrast, coarseness,…) may be quantitatively studied in a similar fashion.

253934	253744	253097	251021	251517
253683	253239	250870	248305	251295
252974	251028	0	251032	252980
251286	248315	250870	253235	253680
251539	251045	253103	253745	253939

Table n. 1 *Discrepancy value Set* $\mathbf{D}_S$.

1.0000	0.9992	0.9967	0.9885	0.9905
0.9990	0.9972	0.9879	0.9778	0.9896
0.9962	0.9885	0	0.9886	0.9962
0.9896	0.9779	0.9879	0.9972	0.9990
0.9905	0.9886	0.9967	0.9992	1.0000

Table n. 2 *Normalized Discrepancy Value Set* $\mathbf{d}_S$.

0.0000	0.0008	0.0033	0.0115	0.0095
0.0010	0.0028	0.0121	0.0222	0.0104
0.0038	0.0115	0	0.0114	0.0038
0.0104	0.0221	0.0121	0.0028	0.0010
0.0095	0.0114	0.0033	0.0008	0.0000

Table n. 3 *Relevance coefficient Set* $\mathbf{R}_S$.

3. ICONIC REPRESENTATION OF DIRECTIONALITY MEASURE.

One of the purposes of the research accounted in this paper is to provide a way to index a texture database using perceptual relevant features. It is immediately evident that to look at the directionality measure matrix is not at all an intuitive modality of interaction for the layman or the graphic professional. There is hence a need for a more visual presentation of the data.

Given the "angular" nature of directionality it is very natural to think to an iconic representation that resembles a dial display. Indeed we have tried several such designs and in this section we present one design that has been proved usable in our experiments.

The usability of our design has been evaluated keeping in mind a special application: enable a graphic professional to formulate in a natural and easy way queries in order to retrieve, from a large texture database, a smaller set of patterns that he may use in his productions.

For sake of exposition in the following we report the description of a "directional dial" for a texture relative only to a set of 5×5 relevance coefficients. Although co-occurrence matrices relative to larger offset sets may be used, the visual information becomes in these cases cluttered and it is not valuable. Moreover we use as a offset the same set S introduced in section 2.

The basic shape of the proposed glyph is made by two concentric circles. This pattern has indeed a natural affordance for the problem at hand. The inner circle is divided by thin segments into eight equal parts. The surrounding ring is instead partitioned into sixteen sectors by radii that are parallel to the elements in the offset set, see fig. 5. Each radial segment is now naturally mapped to each relevance coefficients. To visually represent these coefficients we choose line thickness. Notice that colours, saturation, radii's length could be used to enrich the representation, but we found that the glyph, in this way, became quickly, rather unintuitive.

In figure 6 the glyph relative to the texture in figure 1a shows a clear correspondence between the perceived directionality without ambiguity.

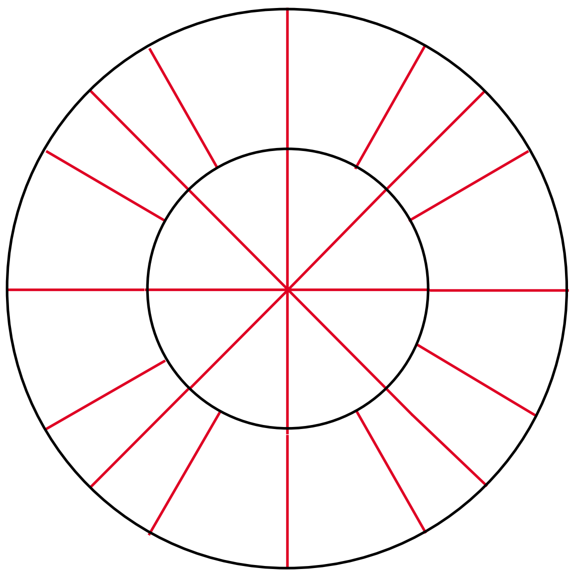


Fig. 5: *The basic shape of the proposed glyph.*

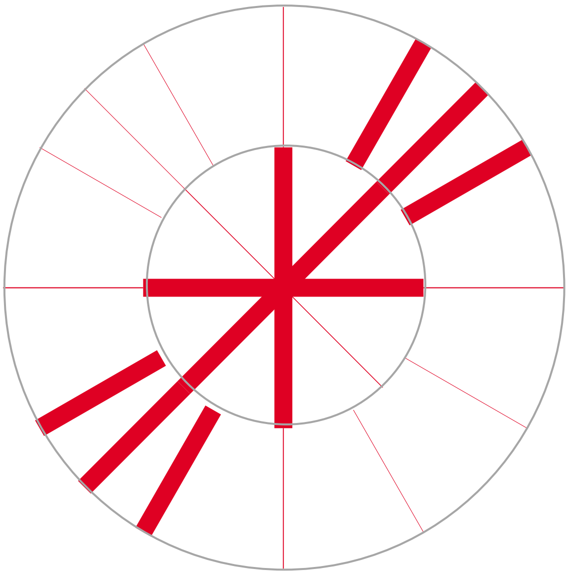


Fig. 6: Glyph corresponding to the texture in fig. 1a.

4. EXPERIMENTAL RESULTS AND VARIATIONS

We have implemented a prototype of the described system using an engine (written in C) that is able to compute the relevance coefficients $\mathbf{R_S}$ from a grey level texture with respect to the directionality measure defined in section 2. These data are themselves input for a visualizer tool (prototypically written in Matlab) who is able to produce glyphs as described in section 3.

Relevance coefficients, as pointed out in section 2, are in the range [0,1]. We have experimented with different mapping functions between [0,1] and thickness range [0.001, R]. The user may interactively select a favorite value for R (default R=10).

The mapping function used to re-scale relevance coefficient values is the linear relation $\mathbf{R'_S} = \mathbf{R_S} * R + 0.001$.

This very simple solution does not generally produce good results because relevance coefficient are not uniformly distributed in the unit interval. For this reason we have proposed other two mapping function: exponential and contrast stretching. Below we only discuss the contrast stretching mapping function.

This is obtained as follow:

$$f(t)=\begin{cases} 0.01+t/(M-\sigma)*0.1 & \text{if } 0 \le t < M-\sigma \\ 0.11+(t-M+\sigma)/(2\sigma)*0.69 & \text{if } M-\sigma \le t < M+\sigma \\ 0.8+(t-M-\sigma)/(1-M-\sigma)*0.2 & \text{if } M+\sigma \le t \le 1 \end{cases}$$

where M=mean($\mathbf{R_S}$) and σ=variance($\mathbf{R_S}$).

The glyph in fig. 6 has been obtained using the contrast stretching function, as well as the set the set of texture together depicted in fig. 7 together with the correspondent set of glyphs. Almost all glyphs capture effectively the preferred direction of the input texture.

Another important issue in texture analysis is its resolution scale. Indeed relevance coefficients relative to offset family S change when the offset vectors are homogeneously magnified.

In this case we have built a "composite glyph" made by the juxtaposition of several glyphs like those described before but relative to different resolution scale. Fig. 8 shows such a composite glyph relative to three increasing scales: 1,2,4,6.

Finally we have performed retrieval experiments from a texture database. The results are promising and we have observed a strong dependence of the retrieval quality on the similarity measure between relevance matrices.

Experiments to choose the best suited similarity measure are under development.

5. CONCLUSIONS

In this paper we have advocated a novel approach to texture analysis based on visual

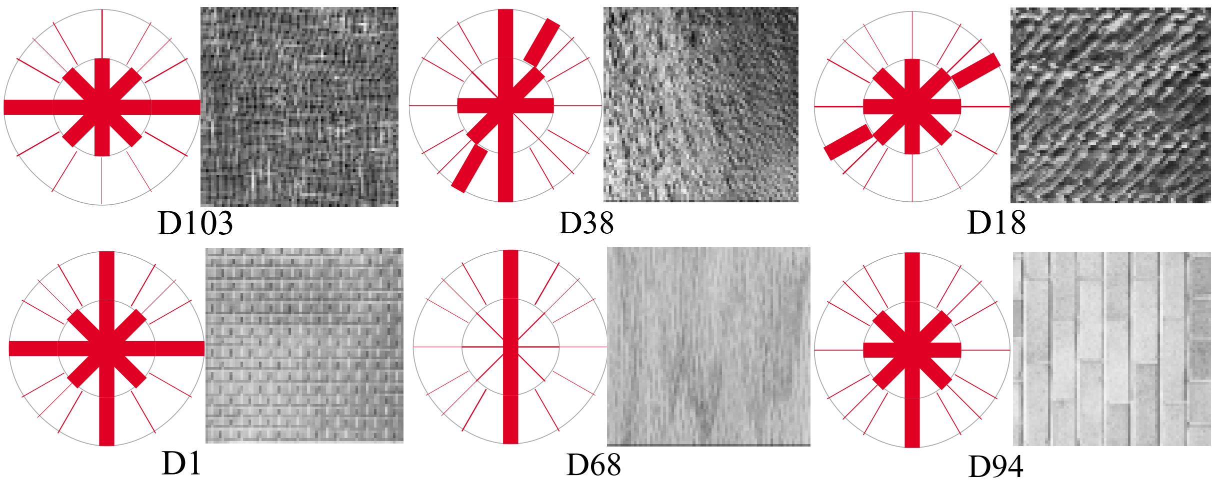


Fig. 7 *A set of six textures (from Brodatz Album* [Broda66a]*) and the correspondent glyphs.*

representation of numerical invariants deduced from co-occurrences matrices.

The encouraging results suggest that other perceptual features of a texture may be represented in a similar fashion.

Future work in this direction will consider contrast, randomness vs. regularity and coarseness vs. fineness.

Also, an exhaustive set of subjective experiments must be done in order to validate perceptually the real performance of the system.

An other relevant application under development is the possibility to formulate interactive queries to a texture database using the proposed iconic representation as a visual query language.

REFERENCES

[Battia00a] S. Battiato, G. Gallo, A Multi-resolution Clustered Approach to Analysis and Synthesis of Texture Images - In Texture Analysis in Machine Vision, Ed. M. Pietikäinen - Series in Machine Perception and Artificial Intelligence - Vol. 40, World Scientific, October 2000.

[Berge93a] J.R. Bergen, B. Julesz, Rapid discrimination of visual patterns, *IEEE Transactions on Systems Man and Cybernetics* 13,pp.857-863, 1993.

[Broda66a] P. Brodatz, Textures: A Photographic Album for Artists &Designers, *Dover, New York*, 1966.

[Burt83a] P.J. Burt, E.H. Adelson, The laplacian pyramid as a compact image code, *IEEE Transactions on Communications*. Vol. 31, pp.532-540, 1983.

[Cross83a] G.R. Cross, A. K. Jain, Markov Random Field texture models, *IEEE, Pattern Anal. Machine Intell.*, Vol 5, pp.25-39, 1983.

[DeBon97a] J.S. De Bonet, Multiresolution Sampling Procedure for Analysis and Synthesis of Texture Images, In *Computer Graphics*, pp.361-368, ACM SIGGRAPH, 1997.

[Diaco81a] P. Diaconis, D. Freedman, On the statistics of vision: the Julesz conjecture, *Journal of Mathematical Psychology*, 24, 1981.

[Efros99a] A. Efros, T. Leung, Texture Synthesis by Non-parametric Sampling – *In Proceedings of ICCV*. Vol.2,Greece 1999;

[Gotli90a] C.C. Gotlieb, H.E. Kreyszig, Texture descriptors based on co-occurence matrices, Computer Vision, *Graphics and Image Processing*, Vol. 51, No.1, pp. 70-86, 1990;

[Haral79a] R.M. Haralick, Statistical and structural approach to texture, *In Proceedings IEEE*, Vol.67, 1979.

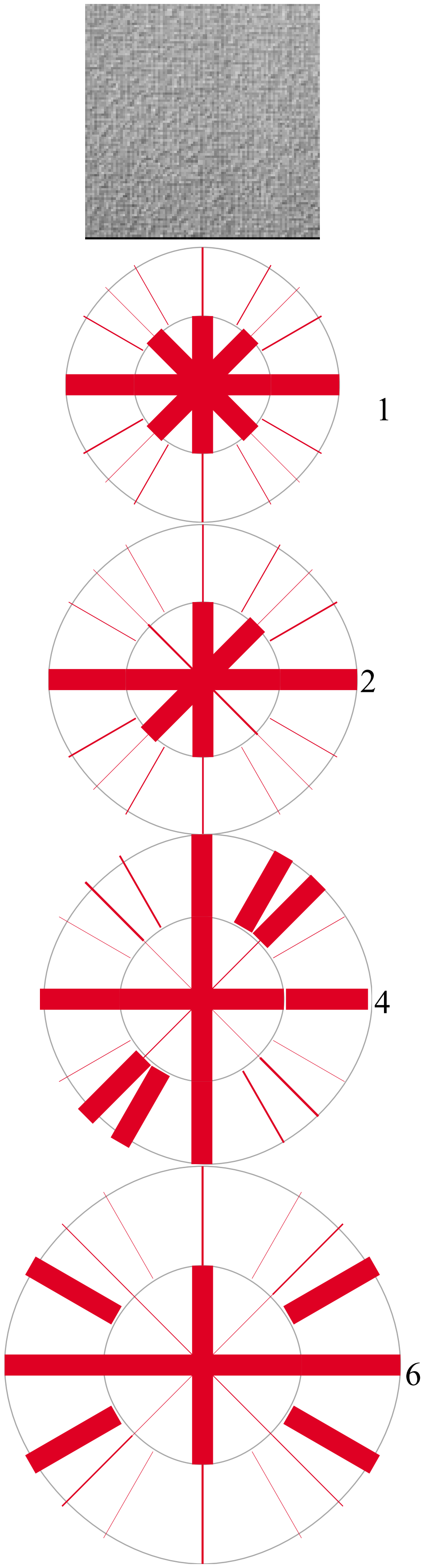


Fig. 8: *A texture with glyphs in different resolutions*

[Heege95a] D.J. Heeger, J.R. Bergen, PyramidBased texture analysis/synthesis, In Computer Graphics, pp. 229-238, ACM SIGGRAPH, 1995.

[Inter00a] V Interrante. Harnessing Natural Textures for Multivariate Visualization, Computer Graphic and Applications, vol 20, No. 6, 2000, pp 6-11

[Jules96a] B. Julesz. Dialogues on perception, *MIT Press*, Cambridge MA, 1995

[Ogden85a] J.M. Ogden, E.H. Adelson, J.R. Bergen, P.J. Burt, Pyramid-Based Computer Graphics, RCA Engineer 30, pp.4-15, 1985.

[Perlin89a] Perlin, E.M. Hoffert, Hypertexture, In Computer Graphics, Vol.23, No.3, pp.253-262, ACM SIGGRAPH, 1989.

[Pratt91a] W.K. Pratt, *Digital Image Processing*, John Wiley and Sons, Inc, 1991

[Rao93a] A. R. Rao, G.L. Lohse, Identifying High Level Features of Texture Perception, *CVGIP: Graphical Models and Image Processing*, vol. 55, No. 3, 1993, pp. 218-233.

[Simon92a]E.P.Simoncelli, W.T. Freeman, E.H. Adelson, D.J. Heeger, Shiftable Multiscale Transform, IEEE Transactions on Information Theory 38, pp.587-607, 1992.

[Tamur78a] H. Tamura, S. Mori, and T. Yamawaki. Texture features corresponding to visual perception. *IEEE Trans. on Systems, Man, and Cybernetics*, 8(6):460--473, 1978.

[Tucer93a] M.Tuceryan, A.K Jain, Handbook of Pattern Recognition and Computer Vision, Ch. Texture Analysis, pp.235-276, *World Scientific Publishing Company*, River Edge, Nj, 1993.

[Weska76a] J. Weszka, C.R.Dyer, A. Rosenfelf, A comparative study of texture measures for terrain classification, *IEEE Trans. Sys. Man. Cybern.*, Vol. SMC-6, 1976.

[Wey00a] L.Y. Wei, M. Levoy – Fast Texture Synthesis using Tree-structured Vector Quantization, *In Proceedings of ACM SIGGRAPH 2000;*

[Winkl95a] G. Winkler, Image Analysis, Random Fields and dynamic Monte Carlo Methods, *Springer-Verlag*, 1995.

[Zhu98a] S. C. Zhu, Y. N. Wu, D. Mumford, Filters, Random fields And Maximum Entropy (FRAME), *Int'l Journal of Computer Vision*, 27(2) 1-20, March/April 1998.

[Zhu00a] S. C. Zhu, X. Liu, Y. N. Wu, Exploring Texture Enesmbles by Efficient Markov Chain Monte Carlo - *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 22, No.6, pp 554-569, June, 2000.