Bridging the Semantic Gap for Texture-based Image Retrieval and Navigation

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Abstract— **In this study, we propose a new semantic approach for interpreting textures in natural terms. In our system, the user can reach desired textures by navigating into a hierarchy of sub collections previously held (offline). The originality of the proposed approach stems from two reasons: *(1)*- the intrinsic properties of the texture features extracted from the co-occurrence matrices have never been used before and *(2)*- it provides some degree of tolerance to generate the classes semantic which is not available with the standard unsupervised clustering algorithms such as *k-means*. Thus, our contibutions in this study are threefold. (1)- Our approach maps low-level visual statistical features to high-level semantic concepts; it bridges the gap between the two levels enabling to retrieve and browse image collections by their high-level semantic concepts. (2)- Our system models the human perception subjectivity with the degree of tolerance and (3)- it provides an easy interface for navigating and browsing image collections to reach target collections. A comparative study with the unsupervised clustering algorithm *k-means* reveals the effectiveness of the proposed approach.**

Index Terms— **Texture features; Image retrieval; Semantic gap; Navigation; Co-occurrence matrices**

I. Introduction

In recent years, large collections of digital images are created from many areas of academia, medical, commerce,*etc.* These collections are obtained either by numerical acquisition tools of real images and scenes or by digitizing existing collections of analogue photgraphs, drawing and painting. Also, storage systems and tools of interconnecting networks have greatly contibuted to provide a wide volume of digital images which are requiring powerful tools for processing and managing large image databases. One way to explore and search in these collections was by keywords. Unfortunately, this method is not feasible with the growing amount of digital images. However, with the early 90's, digital images open the way of content-based image retrieval (CBIR).

CBIR field has become the dynamic subject interesting both industrial and academic communities [1], [2]. Images entered into multimedia databases are indexed automatically by their own low-level visual features. The most commonly used visual features include color, texture and shape [3], [4]. Feature extraction and signature (index) organisation concern the first stage of retrieving images: *indexing process*. The second phase focuses on the search itself. When the user's query is launched, the system performs a similarity measure between the query's signature and those organised in database then returns the most visually closest images to the user's query. A large number of commercial products and academic retrieval systems that have been developed ongoing the last decade such as IBM QBIC [5], MIT Photobook [6], VisualSEEK [7], Virage [8], Netra [9], IKONA [10]. Comprehensive surveys on the feature extraction techniques and systems in CBIR domain can be found in [2]–[4].

The search of images in earlier works which concentrated on color is effective if the images are partially or exactly matching the query. Unfortunately, image retrieval results fail if the images are in addition to color, texture-like models. The richness of the world in textures do not allow to give a unique and formal definition. Despite this difficulty, the use of textures proved its effectiveness and usefulness in many areas such as pattern recognition and computer vision. The diversity of applications and their objectives keep the field of texture analysis in CBIR yet opened for further research.

In 70's, Haralick et al. [11] were the first to propose a statistical method co-occurrence matrices (COM) to solve the classification and description problems of textured images. The co-occurrence method describes the grey-level spatial dependency of two pixels where fourteen numerical features are excerpts to describe different texture properties. Generally, the most works and CBIR systems use only a subset of these fourteen COM-features. Conners and Harlow in [12] and in Lin's system [13] represent texture images by five COM-features including energy, entropy, correlation, local homogeneity and inertia. A competing method to COM-features is the one proposed by Tamura [14] based on psyshological studies on humain perception. Six statistical features are presented by Tamura to describe texture properites including coarseness, contrast, directionality, linelikeness, regularity and roughness. These features are strongly closest to human perception, thus, make Tamura features very attractive in CBIR systems. Such systems are QBIC system of IBM [15] which use the three features coarseness, contrast and directionality to represent texture images. The literature is rich in extraction texture techniques, we refer the reader to surveys [2]–[4].

In spite the rapid increasing of the number of research publications in CBIR domain [16]–[18], extensive experiments on CBIR systems show that the low-level visual features often fail to describe the high-level semantic concepts in user's mind [19]. Describing the low-level features with sophisticated algorithms cannot model adequatly image semantics and have many limitations when dealing with broad content image databases [20] since there is no direct link between these two levels [21]. The discrepancy between the limited descriptive power of low-level image features and the richeness of user semantics is known as the *semantic gap* [3].

Recently, the main issue is how to relate low-level image features to high-level semantic concepts. In other words, research focuses on how to extract semantics from low-level features which approximate well the user interprets of the images content (objects, themes, events). The state of the art techniques in reducing this gap include mainly three categories: (1)- using ontologies to define high-level concepts, (2)- using machine learning tools to associate low level features with query concepts, (3)- introducing relevance feedback (RF) into retrieval process to improve responses under users intention. In this context of reducing the semantic gap, we propose a new approach for semantic interpretation of texture features allowing some degree of tolerance based on the relevance of results.

In figure 1, we give the basic architecture of our proposed system. The system is composed of three major phases: indexing process, mapping process and image retrieval; following, its overview is given.

Texture Analysis: Each texture image in database is represented by an index of 5 COM-features which characterize in this step the low-level statistical properties of texture.

Mapping process: A set of linguistic terms on each parameter is generated through our proposed approach; so that the degree of appearance of each COM-feature can be interpreted as three semantic terms which characterize the high-level semantic concepts of textures.

Similarity Inference: In this step the user's query is expressed as linguistic terms according to the term sets generated by the mapping process. The similarity between the query and a texture image is computed as a logic operator AND (denoted by $\wedge$) between the linguistic terms of query and those of texture image organized in database.

Index Term sets Database: For each texture, its numerical values calculated from Haralick parameters and its linguistic terms generated from the mapping process are stored respectively in index database and term sets database for further applications.

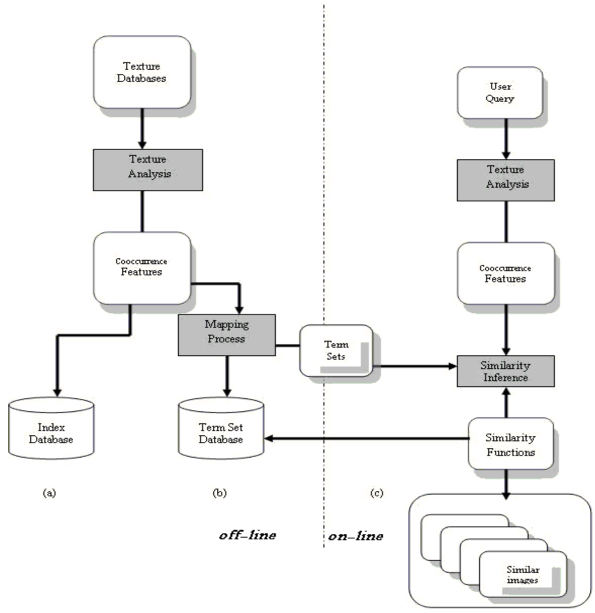

Figure 1. Proposed system architecture: (a) indexing process; (b) mapping process; (c) image retrieval.

The remainder of the paper is organized as follows. In the next section, we focus on image retrieval based mostly on texture and introduce our textural prototype. Section III gives an overview of different ways in narrowing down the semantic gap for textures and presents our proposed approach. Experiments and performance evaluation are presented in section IV. Conclusions are drawn in section V.

II. Indexing Process

Indexing process deals with two steps. Firstly, texture analysis techniques to extract the powerful features of textures. Secondly, the effectiveness way to organize these features into a database to accelerate retrieval images process. In this work, we focus on texture feature extraction based on co-occurrence matrices.

A. Co-occurrence matrices

Several approaches exist for extracting texture features. In this paper, we focus on the co-occurrence matrices (COM). This statistical approach is defined as the joint probability of occurrences of grey-levels i and j between

Figure 2. Co-occurrence matrices corresponding to Brick texture.

pairs of pixels. Each value x at coordinate (i, j) in the matrix reflects the number of occurrence of the grey-levels i and j separated by a given distance d (offset) along a given direction θ. The pair (d, θ) is the key of a COM.

Formally, the definition for an $N \times M$ image f is as follows:

$$P_{d,\theta}(i,j) = \left| \left\{ (n,m) : \begin{array}{r} f(n,m) = i, \\ f(n + d\cos\theta, \\ m + d\sin\theta) = j \end{array} \right\} \right| \quad (1)$$

subsequently normalized:

$$p_{d,\theta}(i,j) = \frac{P_{d,\theta}(i,j)}{N \times M} \quad (2)$$

B. COM selected features

As shown from figure 2, use co-occurrence matrices directly is complicated and not helpful since no information can be drawn. For these reasons, from the fourteen parameters introduced by Haralick [11], we have chosen only four of them including energy, entropy, variance and correlation. More details can be found in [22], [23].

Energy: It refers to global homogeneity of textures. A texture on high energy has a large number of homogeneous areas, whereas a texture on low energy has a small number. Energy (f_{eng})is given as follows:

$$f_{eng} = \sum_{i=0}^{n} \sum_{j=0}^{n} p_{d,\theta}(i,j)^2 \quad (3)$$

where $p_{d,\theta}(i,j)$ is the value of the point (i, j) of the co-occurrence matrix calculated for a distance d and an orientation θ.

Entropy: Generally, entropy is a measure of the dispersion of a distribution. For textures, it refers to texture granularity which means the size and the number of texture primitives. A high value of entropy means a small number of large primitives, whereas a texture on low entropy has a large number of small primitives. Entropy (f_{ent}) is given as follows:

$$f_{ent} = -\sum_{i=0}^{n} \sum_{j=0}^{n} p_{d,\theta}(i,j) \log p_{d,\theta}(i,j) \quad (4)$$

Variance: Variance refers the difference in intensity among neighboring pixels. A high value of variance means a large difference in intensity, whereas a texture on low variance has small difference. Contrast (f_{con}) is given as follows:

$$f_{con} = \sum_{i=0}^{n} \sum_{j=0}^{n} (i - \mu)^2 p_{d,\theta}(i,j) \quad (5)$$

where μ is the mean of co-occurrence matrix.

Correlation: It measures the uniformity of greyscale distribution of pixels. A texture on high correlation has a uniform distribution, whereas a texture on low correlation is non-uniform. Correlation (f_{corr}) is given as follows:

$$f_{corr} = \frac{\sum_{i=0}^{n} \sum_{j=0}^{n} ij p_{d,\theta}(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (6)$$

where μ_x, μ_y are respectively the mean of rows and columns of co-occurrence matrix and σ_x, σ_y are respectively the standard deviation of rows and columns of co-occurrence matrix.

The use of the forth selected COM features in texture retrieval and semantic interpretation is very promising.

III. SEMANTIC TEXTURE-BASED IMAGE RETRIEVAL

Most of the works aim at reducing the semantic gap especially based on texture adopts the technique of Tamura [14] thanks to the semantic properties it offers [24], [25] mainly its strong approximation of human perception. In [26], [27], authors proposed a fuzzy logic CBIR systems for texture queries. In order to bridge the semantic gap, authors use a fuzzy clustering algorithm to interpret each Tamura's feature as five linguistic terms. Thus, a global semantic description of a texture image is a logic composition of different textual descriptions of each Tamura's features. Following this representation of textures, the user can pose queries in terms of natural language or by visual examples, then the system returns the semantically closest images to the query. Hu et al. [28] propose an approach to describe and extract the global texture semantic features using genetic programming. According to Tamura texture model, they utilize the linguistic variable to describe the texture semantics, so it becomes possible to depict the image in linguistic expression such as coarse, fine,*etc*. Then, they use genetic programming to simulate the human visual perception and extract the semantic features value. Li et al. propose in [29] a new clustering scheme called FRD-Clustering to guarantee higher searching quality. By following this scheme, images can be searched by affective concepts, which are derived from Tamura texture space. Affective concepts, which are kind of semantic interpretation on images felt by human, are automatically extracted and represented as FRD (Fuzzy Recognize Degree) within image databases. Using these FRD cluster degrees, the proposed system can support image searching by affective concepts. For example, the affective queries, such as "find cool images" and "find lovely images" can be directly supported based on the semantic features derived from texture information of images.

In this paper, we propose a new method for interpreting texture semantics based on the co-occurrence matrices (COM). Two key points have motivated our choice: The first one concerns the encouraging performance of COM obtained for classification, segmentation and low-level visual image retrieval [23], [30], [31] while the second one involves the originality of our approach. To our knowledge, until that date no research publication has used the intrinsic properties of different COM texture features to express the global texture semantics and reducing the existing gap.

The ongoing works based on COM features (or Tamura features) use either unsupervised clustering algorithms [27], [29] such as *k-means*, *fuzzy c-means* to create blindness semantic classes neglecting the information provided by these features; or using supervised algorithms such as genetic algorithms [28] to simulate the human visual perception. In this case, the user must have a ground truth for learning which is not easy to construct especially when dealing with a general image databases.

A. Our proposed approach

In contrast to the unsupervised standard algorithms, the proposed method is regarded as a unsupervised algorithm that admits some degree of tolerance. This degree allows us to express texture semantics directly form the intrinsic properties of texture features extracted from the COM. Visual texture features retained include energy, entropy, variance and correlation. Based on its degree of appearance, each COM feature is interpreted as three sematic terms: ”*weak, medium, high*”.

Based on our deepest readings and research in image search or other field involving one of the texture parameters previously presented, we built a link between the purely neutral mathematical formula of each COM feature and its own semantic property. The following table summarizes *(*COM feature & semantic property) (tab III-A):

Index	COM feature	semantic property
1	energy	homogeneity
2	entropy	coarseness
3	variance	contrast
4	correlation	uniformity

TABLE I.
SEMANTIC PROPERTIES OF COM TEXTURE FEATURES

The proposed method runs in two phases: (1)- generating semantic classes and (2)- interpretation. The algorithm below details our method:

a) Algorithm: Let f_i the i^th COM feature of n values: $f_i = \left(f_i^1, f_i^2, \ldots, f_i^n\right)$

1) **Generation**
   - sort in ascending numerical values of f_i;
   - define the bounds α_k of semantic classes by a *cutting criterion*:

$$\alpha_k = \overset{argmax}{j} \left\{(f_i^{j+1} - f_i^j) \pm \epsilon : \forall j \in C_k\right\}$$

$$\text{Where} \begin{cases} \alpha_k \text{ is the upper bound of class } C_k \text{ that verify:} \\ \forall k = 1, \ldots, n-1 : 0 < \alpha_k < 1 \end{cases}$$

f_i^j corresponds to the value of the descriptor f_i calculated for the j^{th} image; C_k is the k^{th} semantic class; and ϵ expresses the degree of tolerance.

   - at the first iteration, the bounds α_k are calculated for $\epsilon = 0$; if the expert is satisfied with the semantic grouping of images, the algorithm stops and then the three semantic classes ”weak, medium, high” are resppectively defined by α_1, α_2 and 1. Otherwise the classes will be extended by $(+\epsilon)$ or reduced by $(-\epsilon)$ until satisfying all classes.

2) **Interpretation**

Interpreting a COM feature f_i into semantic term $st(f_i)$ is based on the inference rules (or degree of appearance) given by the equation 7

$$st(f_i) : \begin{array}{l} \mathcal{I} \to \{weak, medium, strong\} \\ I \mapsto \begin{cases} weak \text{ if } f_i(I) < \inf \\ medium \text{ if } \inf < f_i(I) < \sup \\ strong \text{ otherwise} \end{cases} \end{array} \quad (7)$$

The upper $\sup$ and lower $\inf$ bounds are specific of each COM texture feature and correspond respectively to α_1 and α_2.

Therefore, the overall semantics of an image I is expressed as a conjunction of different semantic properties of low-level COM features following equation 8.

$$Sem : \begin{array}{l} \mathcal{I} \to N \times \{weak, medium, strong\} \\ I \mapsto \{(i, st(f_i(I))) : 1 \le i \le n\} \end{array} \quad (8)$$

Following table II shows the experimental values of inf and sup obtained for the four COM texture features:

For example, if the value of the *energy* feature is less

COM feature	inf	sup
Energy	0.02	0.05
Entropy	0.45	0.8
Variance	0.21	0.47
Correlation	0.62	0.92

TABLE II.
Inf AND sup BOUNDS FOR COM TEXTURE FEATURES

than inf and the value of the *variance* exceeds sup, then the semantic interpretation of the image will be ” *weakly homogeneous*” and ”*highly contrasted*”.

Figure 3 shows four semantics texture description examples.

IV. EXPERIMENTS AND EVALUATION

In this section, we will define the experimental settings. The first test concerns evaluation of the ability of approaches to classify semantically textures and the second one is related to image navigation.

A. Unsupervised classification

Performance evaluation is not an easy task which depends on the kind of data and the objectives set by applications. In this section, our goal is to check the ability of our algorithm to cluster textures sharing the same semantics and separate those which are different. We compare our approch with the unsupervised algorithm *k-means*.

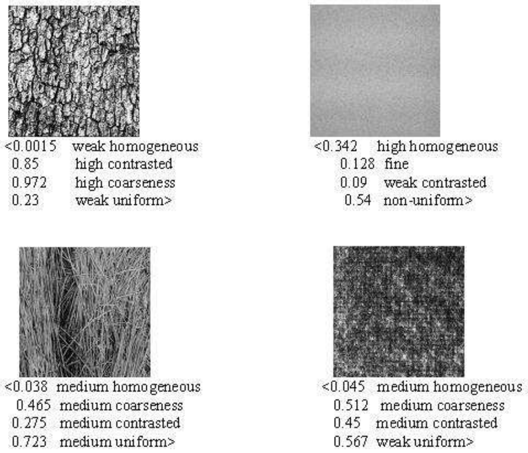

Figure 3. Semantic interpretation of textures.

1) Evaluation metrics: Several evaluation measures are used to evaluate results obtained by classification. In this paper, we select the following criteria: purity classes $\overline{P}$, F-measure and classification error rate T_{err}.

Given a particular cluster C_k of size n_k, the purity P_k of this class is defined to be:

$$P_k = \frac{1}{n_k} \max_i (n_k^i)$$

Where n_k^i is the number of images of the i^{th} class that were assigned to the k^{th} class. The overall purity of the clustering solution is obtained as a weighted sum of the individual cluster purities and is given by:

$$\overline{P} = \sum_{k=1}^{c} \frac{n_k}{n} P_k$$

In general, the larger is the value of purity, the better a clustering approach is. In similar fashion, we use $F-$measure evaluation criterion proposed by Larsen and Aone [32] involving recall ρ and precision π measures: $\rho(i,k) = \frac{n_k^i}{n_{ri}}$ and $\pi(i,k) = \frac{n_k^i}{n_k}$ then the $F-$measure of cluster C_k is the harmonic mean of precision and recall values:

$$F(i,k) = \frac{2 \times \rho(i,k) \times \pi(i,k)}{\rho(i,k) + \pi(i,k)}$$

The overall $F-$measure is given by :

$$F = \sum_i \frac{n_i}{n} \max_i \{F(i,k)\}.$$

The $F-$measure allows two levels of performance evaluation: global (evaluation of all classes) or local (each class is assessed individually). Larger value of F indicates that the clustering algorithm is better.

The last measure is classification error rate T_{err} obtained from the confusion matrix:

$$T_{err} = \frac{\#of misclassified images}{\#of all images}$$

2) Results: Experiments of classification are done for each semantic texture feature taken individually *homogeneity, coarseness, contrasted, uniformity*. Table III summarizes the three measures of performance evaluation tested on the Brodatz album. Generally, we remark that the values obtained with our proposed approach are better than those obtained by k-means. Thus, we conclude that a tolerance degree introduced in the proposed approach improves more semantic classification and interpretation of textures.

B. Semantic texture navigation

Another test is performed to check the capability of the proposed approach to interpret textures semantically. The test responds at the same time to the reduction of the semantic gap between the low-level parameters and the high-level concepts and allow an easy manner to search images by visual navigation (browsing) through an hierarchical structure called "Galois' lattices (concepts lattices)". The interrogation and the search for images in databases can be done in three ways related to information retrieval [33]: (i)- formal query using an appropriate language query for databases; (ii)- by interactive query (called feedback) and (iii)- by navigation. In this work, we opted for the latter mode.

Organizing database and visualization are fundamental to establish a navigation. Many skills of navigation exist [34]. In our case, we opted for the Galois' lattices [35] as a method of structuring images thanks to their dual representation of images and their shared properties in each node of hierarchy and also for their exhaustiveness although this has the disadvantage of considerably slowing down the system when dealing with a large databases. In this work, we are not in this situation because we process the small and the medium image databases as shown in table IV. The total number of extracted semantics properties (nodes) given in the last column grow but not exponentially with a total size of texture image databases.

Image database	# of images	# of nodes
Meastex	60	69
Brodatz	111	109
Brodatz	158	109
Corel	1000	395

TABLE IV.
THE NUMBER OF SEMANTICS PROPERTIES GENERATED BY GALOIS LATTICE.

For visualization, several works are based on a projection of data in 2D or 3D area. The commonly used techniques are the principal component analysis (PCA) [36], projection of Sammon multidimensional scaling (MDS) [37] and Kohonen maps [38]. In this paper, we suggest to browse texture Galois' lattices hierarchy with technique proposed in [34], [35] based on hypertext and hypermedia. Each node in the lattice corresponds to an HTML page with three frames: top, bottom and centre. The top and bottom frames contain fathers and children nodes of the current node. For the central frame, it displays texture images contained in this node. In this context, the user therefore has a high visibility of the images of database, as well as the different semantic classes (grouping in each node). Thus, no formal language to describe query, simply by clicking on pictures (frames

		homogeneity	coarseness	contrasted	uniformity
$\overline{P}$	our approach	0.397	0.789	0.879	0.793
	k-means	0.1245	0.687	0.849	0.756
$F-measure$	our approach	0.578	0.87	0.953	0.645
	k-means	0.6528	0.775	0.79	0.189
T_{err}	our approach (%)	27	14.71	24.07	33.51
	k-means (%)	76.07	73.70	25.40	71.33

TABLE III.
RESULTS OF DIFFERENT METRICS FOR CLASSIFICATION EVALUATION.

on the top and bottom), the user can move up to the target set. The results of navigation on some texture databases are published on the author's website[1].

Figure 4 gives a snapshot of the HTML interface used for navigation. The central node displays images sharing a common set of semantics properties (weak homogeneous, high coarseness and weak uniform). The parent node (above) is considered as a generalisation of concepts, more images and fewer properties. In contrast, for the bottom node is a specification of semantics concepts, fewer images but more shared semantics properties.

V. CONCLUSIONS

The semantic gap between the low-level visual features (color, shape, texture, etc.) and semantic concepts identified by the user remains a major problem in content-based image retrieval. The universality of an approach is proved difficult due to the diversity of applications and approaches. To help reducing this gap, we have proposed a heuristic approach based on the intrinsic properties of texture features extracted from the co-occurrence matrices allowing a degree of tolerance to perform a semantic clustering between classes. The statistical results compared with those obtained by the approach $k-means$ are encouraging and show the effectiveness of our approach to interpretating semantics texture. For the navigation through Galois' lattices, result is also satisfactory.

But, for a non-expert user and which is the case for most users of image retrieval systems, he has a difficulty to give a single interpretation of a texture. Then, we propose for the following work to use a fuzzy logic to support many different semantic interpretation of textures.

REFERENCES

[1] P. Stanchev, "Content-based image retrieval systems," in *In Proc. Bulgarian Comp. Sc. Conf.*, Bulgaria, June 2001.

[2] R. Veltkamp and M. Tanase, "Content-based image retrieval systems: A survey," in *Technical Report UU-CS-*, 2000.

[3] A. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content-based image retrieval at the end of the early years," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 12, 2000.

[4] F. Long, H. Zhang, and D. Feng, *Fundamentals of content-based image retrieval*. Multimedia Information Retrieval and Management, Springer, 2003.

[5] M. Flickner, H. Sawhney, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, D. Steele, and P. Yanker, "Query by image and video content: The qbic system," *IEEE Computer*, vol. 28, no. 9, pp. 23–32, 1995.

[6] A. Pentland, R. Picard, and S. Scarloff, "Photobook: Content-based manipulation of image databases," in *In SPIE Storage and Retrieval for Image and Video Databases II*, vol. 2185, no. 1, Feb. 1995, pp. 34–47.

[7] J. Smith and S.-F. Chang, "Visualseek: A fully automated content-based image query system," in *ACM Multimedia*, 1996, pp. 87–98.

[8] A. Gupta and R. Jain, "Visual information retrieval," *Commun. ACM*, vol. 40, no. 5, 1997.

[9] W.-Y. Ma and B. Manjunath, "Netra: A toolbox for navigating large image databases," *Multimedia Systems*, vol. 7, no. 3, pp. 184–198, 1999.

[10] N. Boujemaa, J. Fauqueur, M. Ferecatu, F. Fleuret, V. Gouet, B. Saux, and H. Sahbi, "Ikona for interactive specific and generic image retrieval," *Proceedings of International workshop on Multimedia Content-Based Indexing and Retrieval (MMCBIR'2001)*, 2001.

[11] R. Haralick, P. Dinstein, and K. Shanmugam, "Textural features for image classification," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. SMC-3, pp. 610–621, November 1973.

[12] R. Conners and C. Harlow, "A theoretical comparison of texture algorithms," *PAMI*, vol. 2, no. 3, pp. 204–222, May 1980.

[13] H.-C. Lin, L.-L. Wang, and S.-N. Yang, "Regular-texture image retrieval based on texture-primitive extraction," *Image Vision Comput.*, vol. 17, no. 1, pp. 51–63, 1999.

[14] H. Tamura, S. Mori, and T. Yamawaki, "Texture features corresponding to visual perception," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 8, no. 6, pp. 460 – 473, 1978.

[15] W. Niblack, R. Barber, W. Equitz, M. Flickner, E. Glasman, D. Petkovic, P. Yanker, C. Faloutsos, and G. Taubin, "The qbic project: Querying images by content, using color, texture, and shape," in *Storage and Retrieval for Image and Video Databases (SPIE)*, 1993, pp. 173–187.

[16] J. Dowe, "Content-based retrieval in multimedia imaging," in *Proc. SPIE Vol. 1908, p. 164-167, Storage and Retrieval for Image and Video Databases*.

[17] C. Faloutsos, R. Barber, M. Flickner, J. Hafner, W. Niblack, D. Petkovic, and W. Equitz, "Efficient and effective querying by image content," *Journal of Intelligent Information Systems*, vol. 3, no. 3-4, 1994.

[18] H. Zhang and D. Zhong, "Scheme for visual feature-based image indexing," in *Proc. SPIE, Storage and Retrieval for Image and Video Databases III*.

[19] X. Zhou and T. Huang, "Cbir: from low-level features to high-level semantics," in *Proc. SPIE Vol. 3974, p. 426-431, Image and Video Communications and Processing 2000*.

[20] A. Mojsilovic and B. Rogowitz, "Capturing image semantics with low-level descriptors," in *Proceedings of the ICIP*, September 2001, pp. 18–21.

[21] I. Sethi, I. Coman, and D. Stan, "Mining association rules

[1] http://idrissi-nj.freehostia.com/

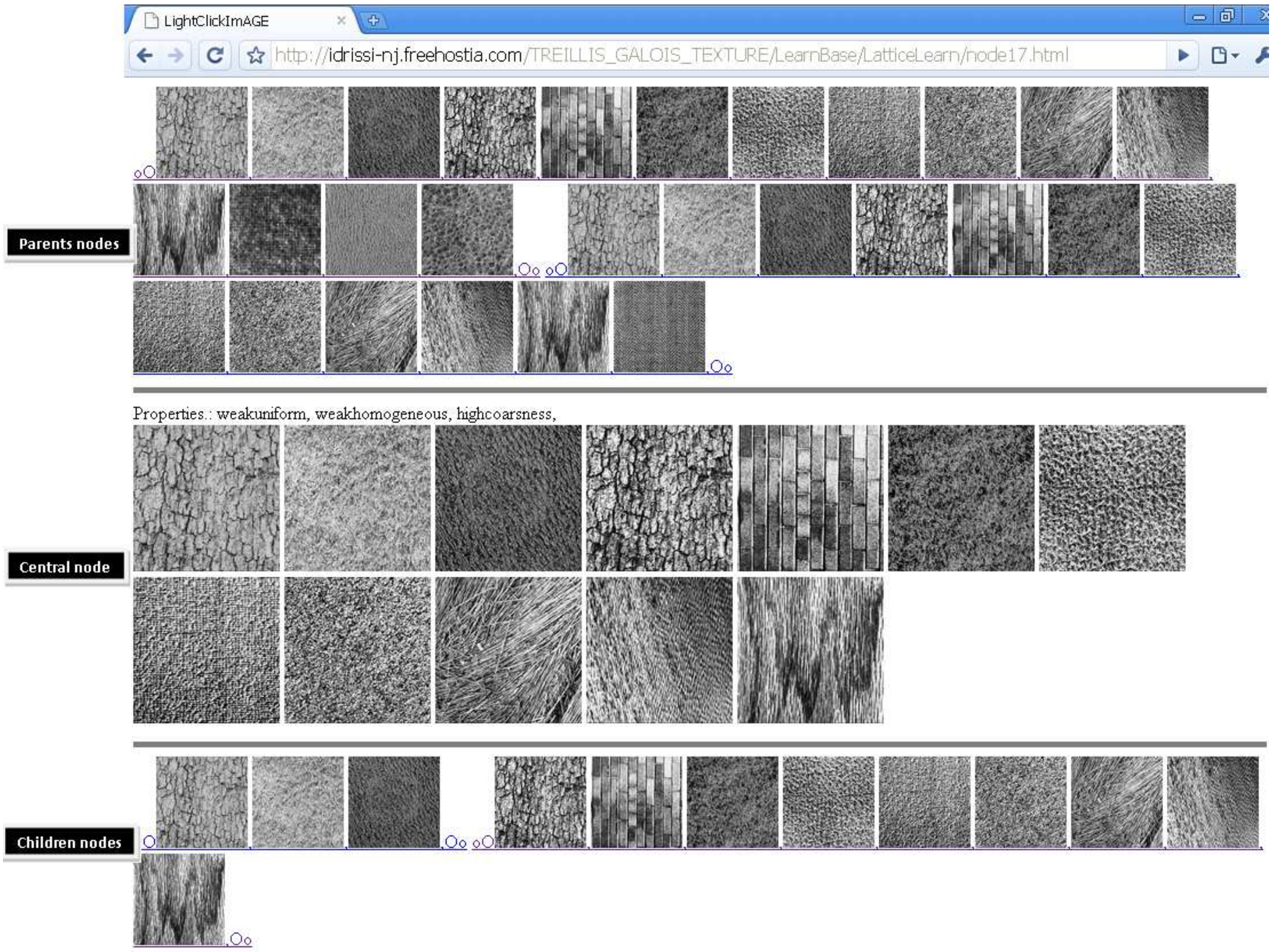

Figure 4. A snapshot of HTML interface corresponding to node with "weak homogeneous, high coarseness and weak uniform".

between low-level image features and high-level concepts," in *Proc. SPIE Vol. 4384, p. 279-290, Data Mining and Knowledge Discovery: Theory, Tools, and Technology III*.

[22] A. DelBimbo, *Visual Information Retrieval*. San Francisco, CA: Morgan Kauffman, 1999.

[23] N. Idrissi, J. Martinez, and D. Aboutajdine, "Selecting a discriminant subset of co-occurrence matrix features for texture-based image retrieval." in *ISVC*, 2005, pp. 696–703.

[24] E. Broek, P. Kisters, and L. Vuupijl, "Content-based image retrieval benchmarking: Utilizing texture categories and texture distributions," *Journal of Imaging Science and Technology*, vol. 49, 2005.

[25] Y. Liu, D. Zhang, G. Lu, and W.-Y. Ma, "A survey of content-based image retrieval with high-level semantics," *Pattern Recognition.*, vol. 40, no. 1, 2007.

[26] H.-C. Lin, C.-Y. Chiu, and S.-N. Yang, "Linstar texture: a fuzzy logic cbir system for textures," in *ACM Multimedia*, 2001, pp. 499–501.

[27] S. Kulkarni and B. Verma, "Fuzzy logic based texture queries for cbir," in *ICCIMA '03: Proceedings of the 5th International Conference on Computational Intelligence and Multimedia Applications*, 2003.

[28] Q. Li, H. Hu, and Z. Shi, "Semantic feature extraction using genetic programming in image retrieval," in *ICPR '04: Proceedings of the Pattern Recognition, 17th International Conference on (ICPR'04) Volume 1*, 2004.

[29] H. Li, J. Li, J. Song, and J. Chen, *A Fuzzy mapping from Image Texture to Affective Thesaurus*, 2007, vol. 4688.

[30] J. Buf, M. Kardan, and M. Spann, "Texture feature performance for image segmentation," *Pattern Recogn.*, vol. 23, no. 3-4, 1990.

[31] J. Strand and T. Taxt, "Local frequency features for texture classification," *Pattern Recognition*, vol. 27, no. 10, pp. 1397–1406, October 1994.

[32] B. Larsen and C. Aone, "Fast and effective text mining using linear-time document clustering," in *Knowledge Discovery and Data Mining*, 1999, pp. 16–22. [Online]. Available: http://citeseer.ist.psu.edu/larsen99fast.html

[33] W. Frakes and R. Baeza-Yates, *Information Retrieval: Data Structures & Algorithms*. Prentice-Hall, 1992.

[34] J. Martinez, "An hypermedia framework for visualising database contents," in *17èmes Journées Bases de Données Avancées, BDA 2001*, 2001.

[35] J. Martinez and E. Loisant, "Browsing image databases with galois' lattices," in *ACM Symposium on Applied Computing (SAC)*, 2002, pp. 791–795.

[36] B. Moghaddam, Q. Tian, and S. Huang, "Spatial visualisation for content-based image retrieval," in *ICME2001*, Waseda University, Tokyo, Japan, 2001.

[37] Y. Rubner and C. Tomasi, *Perceptual Metrics for Image Database Navigation*, 1999.

[38] T. Kohonen, *Self-Organizing Maps*, 1995.