HIGH RESOLUTION IMAGERY RETRIEVAL ON THE BASIS OF SKETCH-MODELLING

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KEY WORDS: Environment, Monitoring, Retrieval, Global-Environmental-Databases, Model, Content-based, High resolution

ABSTRACT:

Recent technological advances have made it possible to process and store large amounts of image data. The most impressive example is the accumulation of image data in scientific applications such as satellite imagery. However, in order to realize their full potential, tools for efficient extraction of information and for intelligent search in image data bases need to be developed. The paper describes a new approach to image data retrieval that allows queries to be composed of textured patterns. The textured pattern is converted into a feature representation of reduced dimensionality which can be used for searching similar-looking patterns in the database. This representation is obtained by the texture sketch model based on Gibbs random field approach for high resolution satellite imagery. Experimental results are presented, which illustrate that the proposed representation preserves the perceptual similarities, and provides an effective tool for content-based satellite image retrieval. As well visual and manual image-interpretations produce similar outlines of geographical units.

1. INTRODUCTION

Content-based image retrieval has been a topic for research in the last decades. A number of overviews on image database systems and image retrieval have been published, see e.g. (Veltkamp, 2001; Braveen, 2009). Despite of ongoing research and numerous studies, no effective features have as yet been generally accepted for image retrieval from currently available satellite image data base (SIDB), especially high resolution SIDB (HRSIDB). Quite a few investigations on satellite image retrieval systems are focused on either retrieval by keywords (Smith, 1996) or discerning of very specific features (Kelly, 1995; Wang, 2001). To query an image in accords to user-defined pattern, a pattern's attribute vector that typically relates to 3 descriptive characteristics (i.e. color, shape and texture) is calculated. The next step implies similarity pattern retrieval.

Different Geographical Units to be identified or Mapped (GUMs) differ by their contents in SIDB . Depending upon the specific aim of an interpretation, a GUM may be for example a vegetation patch, a part of the sea surface with a uniform wave pattern, a patch of homogeneous land-use and so on.

Color characteristics (histograms) don't allow for spatial delimitations ; therefore, color histogram based image retrieval of (HR)SIDB-images often leads to erroneous query results. One can hardly obtain effective query results by the use of shape characteristics, since shapes of natural GUMs are extremely diverse and complicated. GUMs presented in SIDB by more or less homogeneous patterns in grey level scale, which are decisive for content-based image retrieval. Spatial homogeneity of GUMs in high resolution imagery is directly related to their textural features**.**

The presented research aims at

1. a formalised description of textural features, and
2. the development of a model presentation that describes homogeneity of textural patterns in terms of probabilistic self-similarity.

The results of content-based image retrieval using the proposed model, are also presented in this paper.

2. SKETCH TEXTURE MODEL

Precise definition of texture doesn't exist yet that is evidence of the term complexity. Texture (from Latin *textura* means "weaving" or "structure") relates to the specific structure of visual or tactile characteristics of individual objects (Gimel'farb, 1999). In a broad sense, texture defines the structure of an object with respect to the pattern along which its components are arranged. For human perception, texture is the specific, spatially repeated (micro- and macro-) structure: the spatial arrangement of major surface components.

For satellite imagery the texture is presented as spatial interactions of raster elements and their spatial arrangement. Visually, such spatial interactions are presented as repeated changes of grey levels in a proximity window. The Gibbs/Markov models of piecewise-constant regions of the Earth surface are an effective representation of textural objects (Kovalevskaya, 2002). In fact, these models are rather flexible; they allow to "seize" essential parts of visual information presented by piecewise-homogeneous images. The key parameters of the Gibbs model for obtaining metadata of visual pattern content are the following:

1. the size of the proximity window of neighbouring pairwise elements,
2. the structure of neighbouring elements representing major visual pattern content,
3. the significance of each element in the structure**.**

Let us suppose that natural textures in high resolution images possess a spatial self-similarity that can be expressed as the frequency of pairwise elements. Probabilistic self-similarity of a homogeneous texture pattern means that all probable combinations of signals in pairwise cliques are considered as having different likelihood of occurrence on the textural pattern (Gimel’farb, 1999). Then, one can state that *two patterns are* *similar in visual sense – so they represent GUMs of the same class –* if they have the same distribution of signal pairs in cliques of the same type.

Let us assume, the more frequent a combination of signals for a paiwise cliques $\boldsymbol{r}$, the greater distance is observed between the pattern's marginal frequencies and the marginal frequencies of an independent random field (IRF). Therefore, texture sketch corresponding to pattern $\boldsymbol{S=s}$ can be defined as follows:

$$\textbf{\textit{Sketch}}\ (\boldsymbol{S=s}\,|\,\boldsymbol{w}) = \\ =\{r^*\in \boldsymbol{R}:\ Dist(\mathrm{H}_{r^*}(\boldsymbol{d}|\ \boldsymbol{s}),\mathrm{MF}(\boldsymbol{d}))\geq TRESH_{Sketch}, r\subset\boldsymbol{R}\}, \qquad (1)$$

where $\boldsymbol{R} = ((m,n):\ m=0,...,M\text{-}1;\ n=0,...,N\text{-}1)$ is the finite 2-D lattice of the size $|\boldsymbol{R}|=M{*}N$,
$Dist(\cdot,\cdot)$ is the given type of distance between distributions,
$\mathrm{H}_{r^*}(\boldsymbol{d}|\boldsymbol{s})$ – grey level difference histogram for clique $\boldsymbol{r^*},\ \boldsymbol{d}\in\boldsymbol{D}$,
$\mathrm{MF}(\boldsymbol{d})=(|\boldsymbol{Q}|\text{-}abs(\boldsymbol{d}))/|\boldsymbol{Q}|^2$ are marginal frequencies of IRF,
$\boldsymbol{Q} = \{0,1,\ldots,q_{max}\}$ is a finite set of grey levels q in lattice sites (m,n),
$\boldsymbol{D}=\{-q_{max},\ldots,0,1,\ldots,q_{max}\}$ – a set of grey level differences,
$\boldsymbol{w}$ - the given proximity window,
$TRESH_{Sketch}$ - the threshold for types of the sketch cliques.

The application of the model (1) also means the implicit use of perceptional data. It is evident that the more pronounced is the linearity, regularity, orientation, etc. of textural pattern, the greater will be the visual dissimilarity between the pattern and an IRF.

Experiments with several textures allow to propose the following steps to get texture sketch (Gimel'farb, 1999):

1. Compute grey level difference histograms for all cliques in the proximity window**.**
2. Compute the distances between the grey level difference histograms and marginal frequencies of IRF.
3. Find the clique family, which differs the least from the IRF (that is, corresponds to the least distance).
4. Compute the distances between the grey level difference histograms and the clique family found in 3.
5. Compute the average distance *AvDist* and standard deviation *STD* of the distances in 4.
6. Compute the threshold $TRESH_{Sketch} = AvDist + STD$.
7. Choose the clique families whose distances exceed this threshold to represent the sketch.

Experiments to obtain texture sketch were carried out using two types of model patterns:

1. Dissimilarity patterns allowing instantaneous (not exceeding 200ms at a moment) separation from each other (Marr, 1982)**.**
2. Similarity patterns allowing to make separation only after thorough study.

Table 1 represents sets of patterns according to the expert classification (Ma, 1996) and contains significant structures for diverse proximity; the importance of each element in the structure is denominated by means of grey level, namely: the darker raster structure element, the higher its significance for visual content representation is. The outcomes of experiments are evidence of strong similarity in sketches of the same class patterns (class 1, Table 1) or even their full similarity (class 2, Table 1), if class patterns are similar in more than one visual criterion.

To the contrary, if class patterns are similar in one visual criterion, significant elements of patterns demonstrate difference in positions of window $\boldsymbol{w}$ (class 3, Table 1).

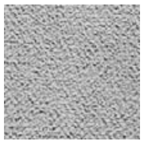
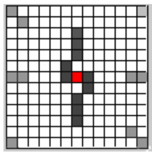
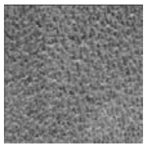
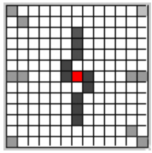
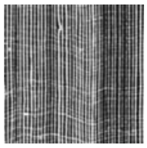
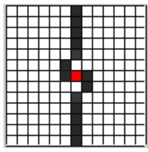
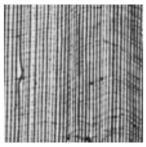
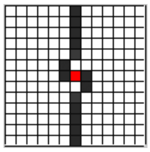
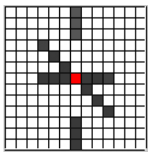
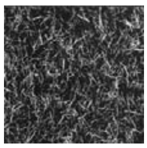
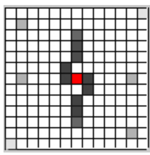
Class #, # in IDB-1	Sketches
 **class 1**, 57	
 **class 1**, D92	
 **class 2**, D106	
 **class 2**, D105	
 **class 3**, 107	
 **class 3**, D108	

Table 1. Classes of similar patterns and corresponding sketches for 13x13 proximity window

The size of a proximity window $\boldsymbol{w}$ depends on the textural pattern. The larger the window, the more accurate estimate of the texture sketch will be, but also the slow will be the search in SIDB. So the choice of the size of a proximity window should be based upon a reasonable compromise between computational power and representativeness of the sketch.

In particular, for 220x110-patterns a 9x9-window gives already acceptable results. It appeared to be possible to increase the size of the window even to 13x13 (Table 2).

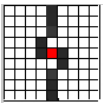
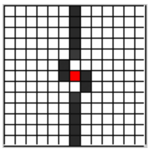
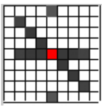
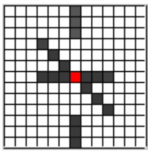
class #, # in IDB-1 (Table 1)	Sketches	
	9x9 window	13x13 window
class 2, D105		
class 3, D107		

Table 2. Sketches for proximity windows of different sizes.

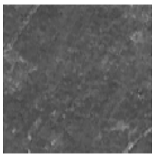
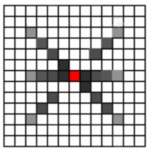
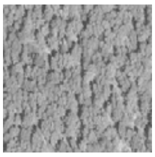
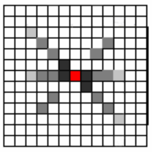
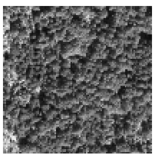
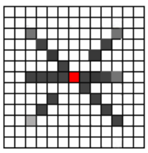
Samples of pine forest	Satellite, resolution, band	Sketches
	Landsat 30 м 0,78-0,90	
	Ikonos 1 м 0,445-0,90	
	QuickBird 0,7 м 0,445-0,90	

Table 3. Pine forest samples and sketches for different resolutions.

It turns out that the property to seize visual information, if patterns are similar in more than one criterion, is sufficient for making comparison of natural objects:

1. Referred to the same class and received with different resolution (Table 3).
2. Referred to different classes and received with the same resolution (Table 4).

In addition, one significant thing was revealed, i.e. spatial position and quantitative composition of raster elements essential for visual representation of a homogeneous region remain the same even at a big change of visual detail(Table 3).

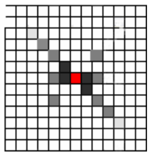
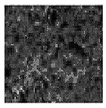
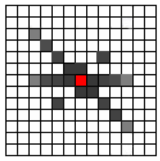
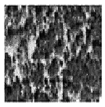
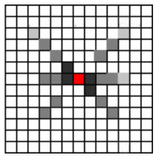
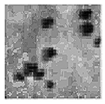
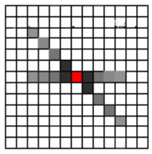
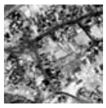
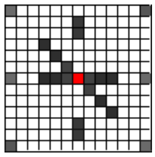
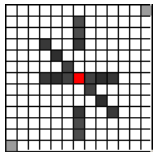
Samples	Sketches	Samples	Sketches
 manufactur ed forest		 deciduous forest	
 rare forest with sand		 glade with trees	
 resident sites		 dachas	

Table 4. Quickbird-samples and corresponding sketches.

3. CONCEPTUAL QUERY IN IMAGE DATA BASE

The sketch (1) of textural pattern is the characteristic of the pattern that allows us to discern different textures. The measure of visual dissimilarity can be used for the arrangement of all images in image data base (IDB) in order of increasing similarity with the query pattern as follows:

1. Enter the query spatial-homogenous pattern ***s***.
2. Retrieve the pattern sketch in accord with the model (1).
3. Calculate measures of dissimilarity $Dist(\boldsymbol{s_t},\boldsymbol{s})$ between the query pattern and images $[\boldsymbol{s_t}\boldsymbol{:}\ \boldsymbol{t=1,2,\dots}]$ from IDB.
4. Choose image $\boldsymbol{s_{t*}}$ with the least value of dissimilarity measure as the first retrieval result:

$$\boldsymbol{Dist}(s_{t*},s)=\min_{s_t\in IDB}\{\boldsymbol{Dist}(s_t,s)\}$$

Choose the subsequent retrieval results by ranking the values $Dist(\boldsymbol{s_t},\boldsymbol{s})$ in increasing order.

The experiments were carried out with two IDBs:

1. IDB-1 that contains the patterns of Brodatz textures (Brodatz, 1966). The pattern classification for 32 classes was taken as a basis for visual comparison of results of IDB-1 queries (Ma, 1996). The classification of various groups of experts can be different; therefore, the experiment was followed by certain changes in the set of classes as a result of the self-training of retrieval system.
2. IDB-2 that contains 64 patterns of high resolution image (Quickbird , 0.7m) and grouped together into 12 classes of GUMs as follows: bushes, resident sites,

forest, meadow, tilled sites, shrub bogs, abandoned mines, bushes with open forest, mire, river bank, floodplain, saline sites.

All experiments proposed that if the first result of retrieval referred to the same class of GUMs as the query pattern, the result was correct.

In experiments with IDB-1 the fixed number of images for the given patterns was retrieved. As for IDB-2, the retrieval was stopped as soon as all GUMs relating to the same class as the query pattern were received.

Table 5 gives the results of the first queries to IDB-1. Though IDB-1 represents a relatively complex variant for visual retrieval due to ambiguity of objects division into classes, the retrieval results turned out to be rather encouraging. About 90% of queries show the correct result as the first choice of retrieval system. The first two results are correct for more than 65% of queries, and more than 40% of queries showed the first, second and the third retrieval results to be correct.

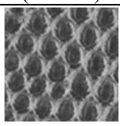
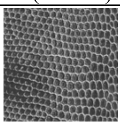
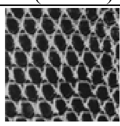
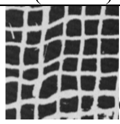
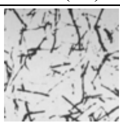
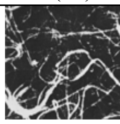
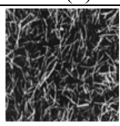
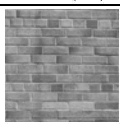
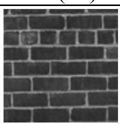
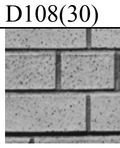
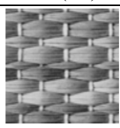
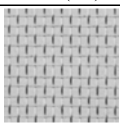
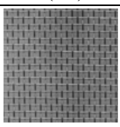
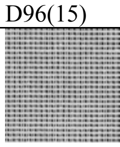
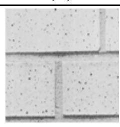
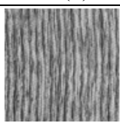
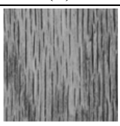
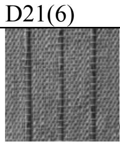
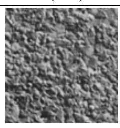
query pattern (class #)	1st retrieved pattern (class #)	2nd retrieved pattern (class #)	3rd retrieved pattern (class #)
 D35(20)	 D3(20)	 D22 (20)	 (*) D104 (3)
 D109(29)	 (*) D107(30)	 (*) D108(30)	 D110(29)
 D94(16)	 D95(16)	 (*) D96(15)	 D56(2)
 D6(1)	 D14(1)	 (*) D21(6)	 D25(15)
 D76(14)	 D68(14)	 (*) D85(23)	 D4(18)

Table 5. Retrieved patterns for IDB-1.

The retrieval system described was found capable of user training. Though some retrieval results (marked by (*) in Table 5) show the incorrect result in accordance with the original classification in (Ma, 1996), *in fact, they are visually similar to the query pattern* by one visual criteria or other. Thus, according to the original classification, the pattern D104(3) refers to the 3rd class, but the retrieval demonstrated the visual resemblance of this pattern to D35(20) from the 20th class. It means that both patterns can be integrated into one class by certain visual criteria, which was not accounted in the original classification.

In a like manner, the system found new features of visual resemblance for pairs D109 and D107, D109 and D108, D94 and D96, D6 and D21, D76 and D85 that were not included in original classification, but these features are correlated with perception.

The experiments with the patterns taken from high-resolution images and represented in Table 6 turned out to be more optimistic when compared to the results with model patterns from IDB-1. In 50% of cases the system "chose" **all possible** patterns of the corresponding class, namely, bushes, bushes with light forest, resident sites, tilled sites, forest, and meadows as the first retrieval results.

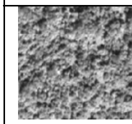
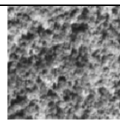
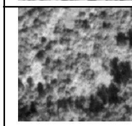
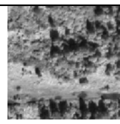
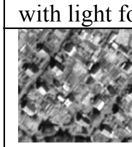
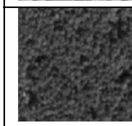
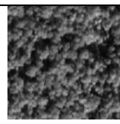
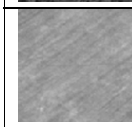
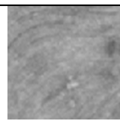
query pattern	1st retrieved pattern	the next retrieved pattern
 bushes	 bushes	2nd – 7th bushes
 bushes with light forest	 bushes with light forest	only 2 patterns in IDB-2
 dachas	 dachas	2nd – 9th dachas
 forest	 forest	2nd – 5th forest
 meadow	 meadow	2nd – 6th meadow

Table 6. Retrieved patterns for IDB-2

4. OUTLINING PIECEWISE-HOMOGENEOUS REGIONS

Experiments were carried out with images received in panchromatic mode from Quickbird (0.7m) and Ikonos (1m) satellites.

The results of the outlining of homogeneous regions according to model (1) as the first step of conceptual retrieval in IDB of high resolution are given in Figure 1, Figure 2. The outlining algorithm was realized by computational comparison of sketches of regions around neighbouring pixels.

5. CONCLUSION

The amount of imagery data increases rapidly, mainly due to the launching of new generation of high resolution satellites (WorldView-1, TerraSAR-X, WorldView-2).

Multiple terabytes of HRSIDB are being collected by many nations across the globe. This raises the question how to retrieve, manage and make best use of the HRSIDB information.

Content-based analysis of all high resolution imagery is a seriously limited by time constraints, and a solution for the content-based image retrieval problem is urgently needed. Also, a new framework is lacking to support content-based search and different levels of analysis and generalization.

Our research proposes a model for homogeneous pattern sketch. The model allows to discern visually meaningful content of a textural pattern. It helps to overcome distinctions between the classes of GUMs in terms of their visual representation.

The experiments show the model parameters' flexibility and the capacity of training and self-training.

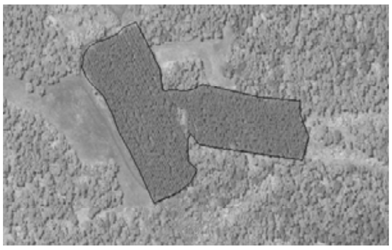
Most importantly, this model can be used for automated generation of interpretation results and metadata, and it offers sufficient computational efficiency to support the formalization of ecological expertise and global-environmental-databases.

(a)

(b)

Figure 1.Outlining homogeneous region of Quickbird-image (0,7m): (a) – according to model (1), (b) - manual..

(a)



(b)

Figure 2.Outlining results of homogeneous region of Ikonos-image (1m): (a) – according to model (1), (b) - manual.

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