Sharing Visual Knowledge in Environmental Information Systems

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Abstract – Remotely sensed data are particularly efficient for environmental mapping in order to outline major environmental types. Some competent models of piecewise-homogeneous images are used in environmental mapping to segment real images. These models consider both an image and a land cover map. Such a pair constitutes an example of a Markov random field specified by a joint Gibbs probability distribution of images and maps. Addition of spatial attributes appears to be necessary in most areas where the differences in spatial data between regions in the image occur. The problem under consideration is sharing visual knowledge about the probable environmental states of different types of land use or development of landscape.

Keywords: segmentation, Gibbs models, texture regions, perceptual sketch.

1. INTRODUCTION

Remote sensing satellites provide a combination of two types of information that can be used to assess landscape behavior - the radiance of the earth's surface on a pixel-by-pixel basis and the spatial variability of radiance due to spatial patterns that can be detected. Spatial data contain information that can greatly increase the potential of remote sensing in landform study. Spatial variability allows us to derive information on vegetation cover, water body morphology, surface roughness inhomogeneity, as well as a method to describe the surface properties of landforms and the state of landscapes in terms of some evolutionary process.

Human observers can effortlessly detect the presence and location of the target elements in a field of distracters. Visual cortex is able to integrate local information from different parts of a visual image into global percepts. Textural information supplies human visual system with many important clues. The local characteristics, such as contrast of orientation, contrast of context, structure of texture elements, etc., describe spatial distribution of contextual interactions and participate in complex perceptual tasks such as texture pop-out and segmentation.

Available methods for environmental mapping do not allow taking into account local interactions and spatial variability within the framework of the unified Bayesian approach. Among the most important characteristic of the segmentation procedure is the homogeneity of objects. Actually, human vision generally tends to divide images into homogeneous areas first, and characterizes those areas more carefully later (Julesz, 1962). The vision-knowledge-based interpretation of environment states by remotely sensed imagery is still more art than a formal theory. It is mostly descriptive, uses fuzzy terms and is not systematically equated with the measurable attributes. The purpose of the study is to gain more insight into the processes of knowledge capture connected with changes in environmental patterns and reformulate this knowledge into quantitative terms.

2. JOINT MODEL OF PECEWISE-CONSTANT IMAGES AND REGION MAPS

Let $\boldsymbol{R} = \{i: i=1,...,M\}$ be a finite arithmetic 2D lattice with ordinal numbering of its sites (pixels) $i \equiv (x_i, y_i)$, $\boldsymbol{IM}=\{IM(i): i \in R; q=IM(i) \in Q\}$ denote an image with a finite set of gray levels Q, and let $\boldsymbol{MP}=\{MP(i): i \in R; l=MP(i) \in \boldsymbol{L}\}$ be a region (land cover) map with a finite set of region labels $\boldsymbol{L}$. Any pair $(\boldsymbol{IM}, \boldsymbol{MP})$, containing the grayscale image and corresponding regional map, is considered as a sample of spatial homogeneous Markov random field (MRF). This MRF is assumed to have only multiple pairwise pixel interactions defined on two identical superposed lattices $\boldsymbol{R}_{IM} \equiv \boldsymbol{R}_{MP} \equiv \boldsymbol{R}$ as we see in Fig. 1.

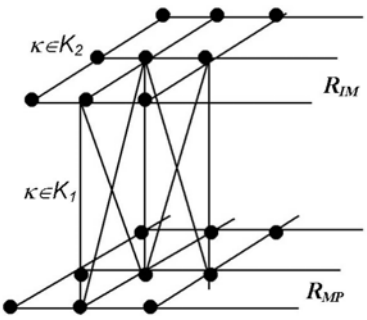


Figure 1. Superposed lattices of image ($\boldsymbol{R}_{IM}$) and map ($\boldsymbol{R}_{MP}$): K_1, K_2 - second-order clique families.

Here a particular case of the piecewise-constant images corrupted by independent random noise is considered. In this case the GPD is as follows:

$$Pr(\boldsymbol{IM},\boldsymbol{MP} \mid \Lambda) = Z^{-1} * exp(-\lambda_1 \sum_{\kappa \in K_1} V_1(IM(i),MP(i):(i)=\kappa) - \\ -\lambda_1 \sum_{\kappa \in K_2} V_2(MP(i),MP(j):(i,j)=\kappa)). \qquad (1)$$

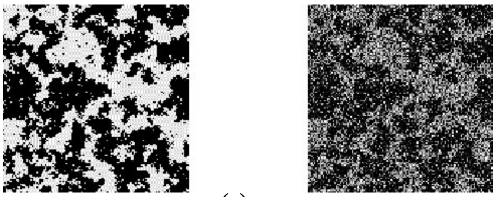
where, Z is a normalizing factor and K_1 and K_2 denote second-order clique families describing the geometric structure of local interactions in the lattice (Geman and Geman,1984). The first family specifies interactions of gray levels and region labels, the other one $K_2=\{\kappa: \kappa=(i,j); i,j \in \boldsymbol{R}; x_i - x_j = \delta_x; y_i - y_j = \delta_y; (\delta_x, \delta_y) \in \Delta\}$, with clique types $\Delta=\{(-1,0), (-1,1), (0,1), (1,1)\}$, specifies pairwise interactions of the region labels. $\Lambda=\{\lambda_a: a=1,2\}$ are control parameters to be learned. Potential functions $V_1(q_i,l_i)$ and $V_2(l_i,l_j)$ on the cliques, assumed to be known in advance, characterize the relative strength of intra-clique interactions between the corresponding gray levels q and/or region labels l.

The following potential functions are used in Eq. (1): $V_1(q_i,l_i) = / q_i - \mu(l_i) /$ and $V_2(l_i,l_j)=0$ if $l_i=l_j$ and $V_2(l_i,l_j)=1$ otherwise. Here,

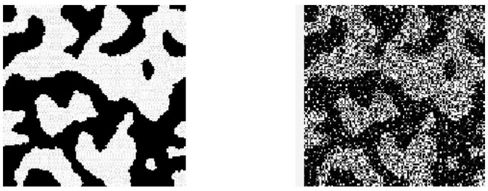
$\mu(l)$ is a noiseless gray level for the region *l*. The parameter λ_1 defines the noise variance assumed to be the same for all the regions. The features of the regions are specified by the parameter λ_2: the higher its positive value, the more regular the regional shapes.

3. EXPERIMENTS WITH SIMULATED IMAGES AND REGION MAPS

The Markov chain of the sample pairs having the GPD of Eq. (1) can be generated by the stochastic relaxation. Each step of the generation involves two successive passes (iterations) over the superposed lattices to form the current map under the fixed previous grayscale image and the current grayscale image under the fixed current regional map. In experiments, these chains reach the quasi-equilibrium state after a rather small number of the iterations.
Examples of the final pairs are shown in Figure 2.



(a)



(b)

Figure 2. Pairs "map *MP* – noisy image *IM* " simulated for the given parameters: (**a**)(λ_1,λ_2)=(0.35, 0.40); (**b**) (λ_1,λ_2)= (0.35, 1.20).

It should be stressed that the simulated images are especially useful since polygon boundaries are unambiguous. The similar noisy piecewise-constant images can be found in practical environmental studies, for instance, using some of the Earth's surface images obtained from multiband scanning radiometers or aerial images.

4. TEXTURE MODEL OF MULTIPLE PAIR-WISE INTERACTIONS

For most uses, the segmentation process should include both tone and texture attribute schemes to insure the greatest accuracy. It is apparent that the addition of texture can improve the accuracy in areas where the features of interest exhibit differences in local variance. For a human, the visual features of a textured area relate mostly to specific spatially homogeneous or piecewise-homogeneous patterns created by "weaving" specific primitive elements, or micro-patterns. Many natural and artificial patterns appear to be modeled adequately by the proposed Gibbs model with multiple pair-wise interactions (Kovalevskaya, 2002). We propose to take into account only second-order statistics or multiple pairwise interactions between the gray levels in the pixels:

$$Pr(\mathbf{IM}|\Pi) = Z^{-1} * \exp\Big(\sum_{\alpha\in A}\Big(-\Pi_{\alpha}\sum_{K_\alpha\in K_\alpha} V_{K_\alpha}(IM(i),IM(j):(i,j)\in K_\alpha)\Big)\Big). \quad (2)$$

Here $K_\alpha = \{\mathbf{R}^2 \ni (i,j)\colon i\text{-}j = (\mu_\alpha, \nu_\alpha)\}$ is the pairwise clique family given by the shifts (μ_α, ν_α) between both pixels in a clique, and $\mathbf{A}$ denotes a set of indices.

The validity of this model can be visually and quantitatively checked by comparing simulated samples with the training one. The spatial homogeneity or piecewise homogeneity of a training sample can also be quantitatively verified by matching sample relative frequency distributions of gray level combinations collected over different patches within the sample.

Analysis of spatial attributes appears to be necessary in most areas where the differences in spatial data between regions in the image occur as we see in Fig.3.

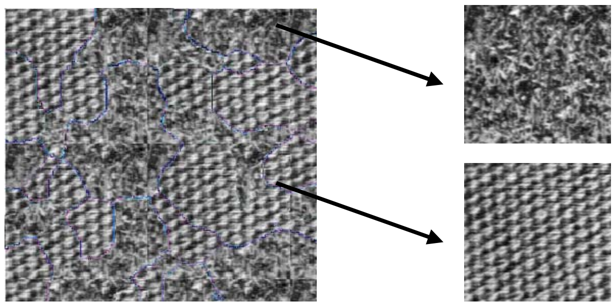


Figure 3. Image of two regions.

A single image region, or a pattern, is assumed to be defined by the homogeneity or translation invariance of the statistics of the image features. A key question of knowledge sharing is what an environment expert perceives from the pattern. More precisely, what are the *sufficient and necessary* features so that a pair of patterns sharing such features can be regarded as the "same class" for different experts. Assume that these conspicuous (highlighting) visual features are perceived to be a *sketch* of the pattern known for an expert. Such *environmental perceptual sketch* (EPS) would have obvious significance for visual knowledge sharing. On computational level the problem of highlighting features' representation means modeling of the pattern homogeneity.

Let us define expert perception of homogeneous pattern of environment as popout of a set of targets, which are situated on the pattern as much regularly as the pattern is homogeneous. In this case an important issue of EPS-modeling is opportunity to be used by natural intelligences in constructing of images and patterns of environment states due to "biological plausibility". The last one means that EPS-model is consistent with previous experimental evidences from another disciplines (Mimford, 1992; Treisman et al, 1980; Scalfia and Joffe, 1995).

It is natural to assume that an expert perceives the most effectively those signals that occur most frequently. Thus, it is statistical properties of the environment that are relevant for sensory processing. On the other hand, environmental patterns contain characteristic statistical regularities that set them apart from purely random patterns, or independent random fields (IRF).

Let us suppose that the more regular form of structure containing in environment pattern, the more effective sketch of the pattern for higher level operations and coding into memory of an expert. There should be a parameter of the EPS-modeling to measure regularity of pattern structure, or distance from IRF-pattern. For example, it's obvious that *Pattern1* is farther from *IRF*-pattern than *Patter2* as we see in Fig.4.

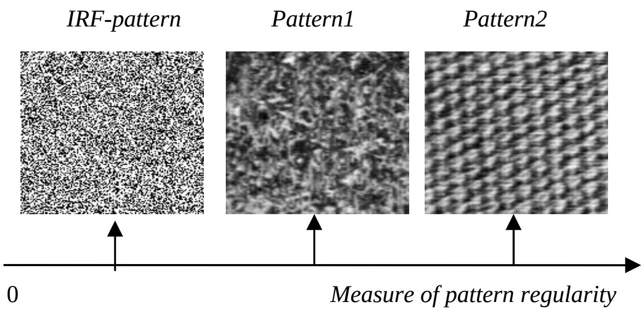


Figure 4. Measure of pattern regularity (non-resemblance with IRF).

In case of EPS-modeling pattern regularity measure, or non-resemblance with IRF, ranges all natural patterns through validation of expert perception comparisons.

The success of *PSP-approach* depends on three choice-issues:

- Choice on model of PSP that enable to adjust the pre-attentive and attentive visual systems on computational level and to represent continuum of visual mechanisms depending on local (long- and short-range) interactions can contribute to global view (Gimel'farb&Kovalevskaya, 1995).
- Choice on the most rich theoretical framework, in which the model ***(A)*** above could be embedded (Kovalevskaya&Pavlov, 2002; Kovalevskaya, 2002).
- Choice on a function (functions) of measure of pattern regularity, or distance from IRF-pattern, which is concerted with model ***(A)*** and theory of optimal decision ***(B)*** as well as expert perception of homogeneous pattern.

Experiments were carried out with the images of Siberia (Russia). Many natural patterns appear to be modeled adequately by the proposed model. The validity of this model can be visually and quantitatively checked by comparing simulated samples with the training one. The spatial homogeneity or piecewise homogeneity of a training sample can also be quantitatively verified by matching sample relative frequency distributions of gray level combinations collected over different patches within the sample.

5. EXPERIMENTS WITH REAL IMAGES

Experiments were carried out with the images of two unique Siberian lakes: Lake Baikal and Lake Teletskoye. Baikal is one of the largest lakes of the world that has been in existence for *25 .million* years. It contains about 1/5 of the world reserves of fresh water. Besides, Lake Baikal is the deepest lake in the world (1641 m). This lake is considered to be a reservoir and factory of high-quality pure water.

Experiments were carried out by using extension of the model described by Eq. (1) onto the multiband images with constant intensity, hue and saturation, and with a fixed number of regions. Comparisons with geographical map and visual experts' interpretation showed that result of Gibbs-model-segmentation is rather effective for identifying and enhancement of the shore outline as well as for shoals and suspended matter detection.

Teletskoye Lake is the largest and the deepest freshwater reservoir in the south of West Siberia. Among all freshwater lakes in Russia it ranks next to Lake Baikal for storage of fresh pure water. Figures 6 show the results of Teletskoye Lake image analysis.

Different fragments of the image were used to analyze how the proposed model described by Eq. (1) and (2) reflects the self-similarity within the patterns. The analysis showed that visual patterns of mountains' images really belong to the class of stochastic textured patterns. In such cases, the natural and simulated patterns possess good visual resemblance and high proximity of the characteristic clique's families.

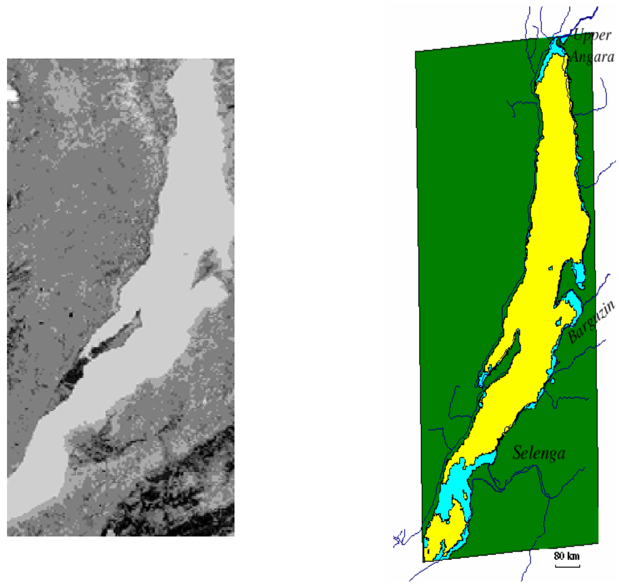


Figure 5. Image of Lake Baikal (Eastern Siberia, 0.72-1.2 μm) and georeferenced map of segmentation from Eq. (1) and (2) – shoals and dense flows with different concentrations of suspended matter, pure water, dry land.

the next stage. PSP-modeling leads to a better understanding of expert capacity for fast categorization of environmental objects.

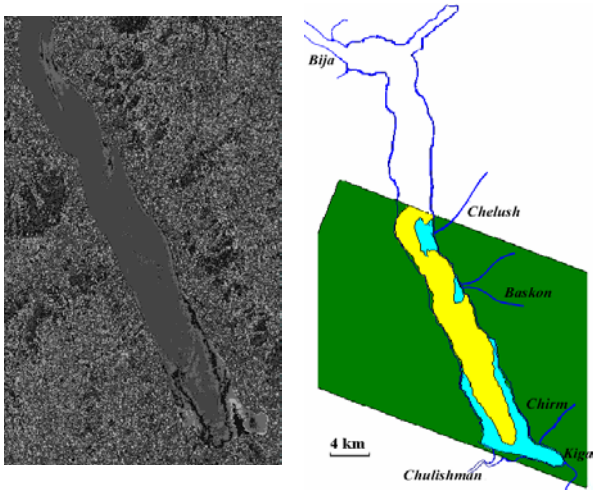


Figure 6. Image of Lake Teletskoye in Altai mountains (Western Siberia, NIR-band) and georeferenced map of segmentation by Eq. (1) and (2) – shoals and water with sediment load and organic matter, pure water, mountains.

6. CONCLUSION

Environmental mapping by remotely sensed imagery can be effectively realized using proposed joint GPD model within a unified framework of Bayesian decision.

The proposed "image – map" model takes into account the local interactions between pixels assumed to represent the properties of environmental objects. Use of pixelwise stochastic relaxation in processing of images described by MRF/GPD models lead to a new scheme of environmental mapping, i.e. multiple processing from different initial maps with results combined at the last stage.

Complexity of environment states makes to develop computational methods of segmentation based on continuum of pre-attentive and attentive mechanisms of vision.

Sharing environmental knowledge can benefit from EPS-approach because such kind of encoding reduces the data rate without significant information loss, moreover the level of loss may be managed by parameters of proposed model. So, significant saving can be made by avoiding transmitting the information redundantly. In this case there is no problem of how does one judge whether or not accept the fit of the environment pattern sketch and decide that the signal does contain a valid sample of the pattern in question.

In fact, the sketch appears to be a concise representation of the environment region and creates more salient locations. So, the model is needed for characterizing the spatial arrangements of the components. The discovery of meaningful components could go away beyond pairwise interactions, including statistics Nth order. For example, triplets, quadruples of elements, etc could be used in the next stage. PSP-modeling leads to a better understanding of expert capacity for fast categorization of environmental objects.

6. REFERENCES

S. Geman, D. Geman (1984): Stochastic Relaxation. Gibbs Distributions, and the Bayesian Restoration of Images. IEEE Trans. Pattern Anal. Machine Intell. 6(6): 721-741.

G. Gimel'farb (1999): Image Textures and Gibbs Random Fields. Kluwer Academic Publishers: Dordrecht, 250 p.

G. Gimel'farb and N. Kovalevskaya (1995): Segmentation of images for environmental studies using a simple Markov/Gibbs random field model. p.57-64. *In* V. Hlavac, R. Sara (eds.). Vol. 970. Proc. Conf. Computer Analysis of Images and Patterns, 6th, Prague, Czech Republic, 6-8 Sep. 1995. Lecture Notes in Computer Science, Springer.

B. Julesz (1962):Visual pattern discrimination. IRE Trans. on Information Theory, 8:84-92.

N. Kovalevskaya (2002): Landscape Indication Based on Stochastic Relaxation, 121-146. *In* Ranian S. Muttiah (Ed.). From Laboratory Spectroscopy to Remotely Sensed Spectra of Terrestrial Ecosystems, Kluwer Academic Publishers.

N.Kovalevskaya and V.Pavlov (2002): Environmental Mapping Based on Spatial Variability, in: Journal of Environmental Quality, 31:1462-1470.

L. Mumford (1992): On the computational architecture of the neocortex, II The role of cortico-cortical. loops, Biological Cybernetics, 66, 241-251.

C.T. Scialfa and K.M. Joffe (1995): Preferential processing of target features in texture segmentation, Perception and Psychophysics, 57, 1201-1208.

A. Treisman and G. Gelade (1980): A feature integration theory of attention. Cognitive Psychology, 12:97--136.