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Comparison of the classification methods for the images modeled by Gaussian Random Fields

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Abstract. In image classification often occur such situations, when images in some level are corrupted by additive noise. Such noise in image classification can be modeled by Gaussian random fields (GRF). In image classification supervised and unsupervised methods are used. In this paper we compare our proposed supervised classification methods based on plug-in Bayes discriminant functions (PBDF) (see [6] and [11]) with unsupervised classification method based on grey level co-occurrence matrix (GLCM) (see e.g. [8] and [1]). The remotely sensed image is used for classification (USGS Earth Explorer). Also GRF with different spatial correlation range are generated and added to the original remotely sensed image. Such situation can naturally occur during forest fire, when smoke covers some territory. These images are used for classification accuracy examination.

Keywords: image classification, Gaussian random fields, supervised classification, Bayes discriminant function, unsupervised classification, grey level co-occurrence matrix.

Introduction

Image classification is a problem of dividing an observed image into several homogeneous regions by labeling pixels based on feature information and information about spatial adjacency relationships with training sample. Switzer [13] was the first to treat classification of spatial data. For features based on Gausian Markov RF model, the influence of texture rotation to image classification is considered by [5]. Spatial contextual classification problems arising in geospatial domain is considered by [10]. Atkinson and Lewis [3] reviewed geostatistical techniques for classification of remotely sensed images.

In the present paper for image classification we use method which is retracting the popular requirement of conditional independence in Bayes classification rules (see [6, 12]). Also the observation to be classified is assumed to be dependent on the training sample. In the series of papers (see e.g., [9, 2, 4]) the incorporation of geostatistical information of features into plug-in versions of classifiers is based on the marginal distribution of the observation to be classified. Thus we investigated the geostatistical Bayes classifiers based on conditional feature distribution of the observation to be classified. The importance and effectiveness of proposed techniques was examined in the examples on images with strictly separated classes corrupted by spatial Gaussian noise (see [12]). In this paper we use proposed techniques for classification of remotely sensed images which classes for classification are not strictly separated before GRF noise is added.

The stationary GRF model for features and MRF model for class labels are considered. For the model mentioned above and in case of known population parameters the error rates associated with PBDF is investigated (see [7, 12]).

In the present paper the comparison of proposed supervised PBDF methods and unsupervised GLCM based classification method is made. The performance is evaluated numerically and visually. For the numerical comparison of the tested classification procedures the empirical errors of misclassification are used.

1 The main concepts and definitions

Suppose that the feature is modeled by Gaussian random field $\{Z(s)\colon s \in \mathcal{D}\}$, $\mathcal{D} \subset \mathcal{R}^2$. In the context of image analysis index s means pixel. The marginal model of observation $Z(s)$ in class Ω_l is

$$Z(s) = \mu_l + \varepsilon(s),$$

where μ_l is the constant mean, and the error term is generated by zero-mean stationary Gaussian random field $\{\varepsilon(s)\colon s \in D\}$ with covariance function defined by model for all $s, u \in D$

$$\operatorname{cov}\bigl\{\varepsilon(s), \varepsilon(u)\bigr\} = \sigma^2 r(s-u),$$

where $r(s-u)$ is the spatial correlation function and σ^2 is the variance.

Let $L = \{1, 2\}$ be the label set, and let $S_n = \{s_i \in D,\ i = 1, \ldots, n\}$ be the set of training pixels (STP). Denote by $Y = (Y(s_1), \ldots, Y(s_n))'$, $Z = (Z(s_1), \ldots, Z(s_n))'$ the labels and features vector, and denote by $T' = (Z', Y')$ the training sample.

Assume that the model of Z for given $Y = y$ is

$$Z = X_y\mu + E$$

where X_y is a design matrix, $\mu' = (\mu_1, \mu_2)$ and E is the n-vector of random errors that has multivariate Gaussian distribution $N_n(0, \sigma^2 R)$.

Denote by r_0 and by R the vector of spatial correlations between Z_0 and Z_n and the matrix of spatial correlations among components of Z_n, respectively. Since Z_0 is correlated with training sample, we have to deal with conditional Gaussian distribution of Z_0 given $T = t$ ($Z = z$, $Y = y$) with means μ_{lt}^0 and variance σ_{0t}^2.

Proposition 1 [Assumption]. *The conditional distribution of $Y(s_0)$ given $T = t$ depends only on $Y = y$, i.e. $\pi_l(y) = P(Y(s_0) = l \mid T = t)$, $l = 1, 2$.*

Under the assumption of complete parametric certainty of populations, the Bayes discriminant function (BDF) minimizing the probability of misclassification (PMC) is formed by log ratio of conditional likelihoods

$$W_t(Z_0; \Psi) = \left(Z_0 - \frac{1}{2}\bigl(\mu_{1t}^0 + \mu_{2t}^0\bigr)\right)\bigl(\mu_{1t}^0 - \mu_{2t}^0\bigr)/\sigma_{0t}^2 + \gamma(y), \tag{1}$$

where $\gamma(y) = \ln(\pi_1(y)/\pi_2(y))$ and $\Psi = (\beta', \theta')'$.

So BDF allocates the observation in the following way: Classify observation Z_0 given $T = t$ to population Ω_1 if $W_t(Z_0, \Psi) \geqslant 0$, and to population Ω_2, otherwise.

Denote the three component vector of parameter estimates by $\hat{\Psi}' = (\hat{\mu}', \hat{\sigma}^2)$.

Then PBDF associated with BDF specified in (1) is

$$W_t(Z_0; \hat{\Psi}) = \left(Z_0 - \frac{1}{2}(\hat{\mu}^0_{1t} + \hat{\mu}^0_{2t})\right)(\hat{\mu}^0_{1t} - \hat{\mu}^0_t)/\hat{\sigma}^0_{0t} + \gamma(y),$$

where $\hat{\mu}^0_{lt} = E(Z_0 \mid T = t,\ Y(s_0) = l) = \mu'_l + \alpha'_0(z_n - X_y\hat{\mu})$, $l = 1, 2$ and $\hat{\sigma}^2_{0t} = V(Z_0 \mid T = t,\ Y(s_0) = l) = \hat{\sigma}^2 R_{0n}$, where for $l = 1, 2$, $\hat{\mu}^0_{lt} = \hat{\mu}_l + \alpha'_0(z_n - X_y\hat{\mu})$, and $\hat{\sigma}^2_{0t} = \hat{\sigma}^2 R_{0n}$. Denote it by PBDFD.

If Z0 is assumed to be independent to T, then PBDF has the following form

$$W(Z_0; \hat{\Psi}) = \left(Z_0 - \frac{1}{2}(\hat{\mu}_1 + \hat{\mu}_2)\right)(\hat{\mu}_1 - \hat{\mu}_2)/\hat{\sigma}^2 + \gamma(y),$$

where $\hat{\mu}$ and $\hat{\sigma}^2$ are the estimates of μ and σ^2, based on $T = t$. Denote it by PBDFI.

2 Numerical example

We have tested our approach on a real world image, namely on areal remotely sensed image obtained with the Landsat7 satellite. The image shows the area from Lithuania territory. We use grey version of the RGB image for the experiment. The crop of the image containing forest and grassland is used. The cropped image dimensions are 500×500 pixels. Here we compare proposed supervised classification methods with unsupervised classification method based on GLCM with relative distance $d = 1$, 32 grey levels, 7×7 window size and relative orientation quantified in four directions $(0°, 45°, 90°, 135°)$ is calculated. GLCM mean is implemented as the texture feature. The sub image of size 100×100 pixels is extracted from the cropped image for classification.

Suppose that original cropped image is corrupted by the noise modelled by GRF with zero mean and Gaussian spatial correlation function given by $r(h) = \exp\{-|h|^2/\alpha\}$ and also belonging to the Matern class. Here α is a spatial correlation range parameter. Such noise can naturally occur from smoke or fog. For supervised classification methods the training sample with $n_1 = n_2 = 30$ is selected and 8 nearest neighbour scheme was used. GLCM are calculated from sub images of size 30×30 pixels using three sub images from forest territory and three images from grassland territory. These GLCM are used as texture examples for classification. The original and corrupted sub images are classified and results using proposed supervised classification methods and unsupervised GLCM method are shown in (Fig. 1)

The empirical errors of misclassification are presented in Table 1. As we can see from the Table 1 the proposed supervised methods perform better then GLCM, especially when GRF is applied. We can see from the Table 1 and from pictures (Fig. 1) that with very small correlation range parameter classification accuracy is not high, but when the range parameter grows bigger accuracy becomes very similar to original image without additive noise.

3 Conclusions

The proposed methods can be used to increase classification accuracy of remotely sensed images when the smoke of fire, fog or other natural situations cover the territory and the correlation range is large.

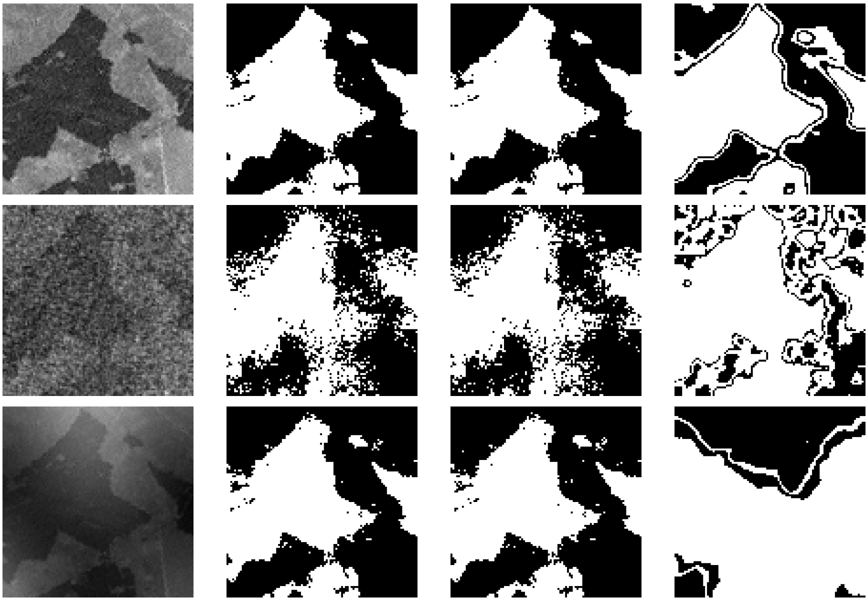

Fig. 1. Images for classification (first column); classification results for PBDF method (second column); results for PBDFI (third column) and results for CM (last column). Original image (first row); image with additive GRF with $\alpha = 1$ (second row); image with additive GRF with $\alpha = 50$ (last row).

Table 1. The empirical errors of misclassification. OI – original image with no GRF added.

α	*PBDF*		*PBDFI*		*GLCM*	
	$\hat{P}(2 \mid 1)$	$\hat{P}(1 \mid 2)$	$\hat{P}(2 \mid 1)$	$\hat{P}(1 \mid 2)$	$\hat{P}(2 \mid 1)$	$\hat{P}(1 \mid 2)$
1	0.213	0.093	0.210	0.093	0.439	0.019
10	0.217	0.073	0.222	0.077	0.323	0.142
50	0.150	0.065	0.054	0.067	0.477	0.265
OI	0.036	0.015	0.036	0.015	0.050	0.035

The results show us the advantage of these methods against unsupervised classification method based on GLCM. Of course we must have in mind that these methods require training sample from the same territory.

The results of performed calculations give us the strong argument to encourage the users do not ignore the spatial correlation and locational information about training sample in image classification.

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REZIUMĖ

Vaizdų, modeliuojamų Gauso atsitiktiniais laukais, klasifikavimo metodų palyginimas

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Vaizdų klasifikavime dažnai sutinkame situaciją, kai, tam tikru lygiu, vaizdai yra sugadinti triukšmo. Toks triukšmas vaizdų klasifikavime gali būti modeliuojamas Gauso atsitiktiniais laukais (GRF). Vaizdų klasifikavime naudojami metodai su mokymu ir be mokymo. Šiame straipsnyje lyginami mūsų pasiūlyti klasifikavimo su mokymu metodai, paremti įterptomis Bajeso diskriminantinėmis funkcijomis (PDBF) (žiūrėti [6] ir [12]) su klasifikavimo be mokymo metodu paremtu pilkumo lygio pasikartojimų matricomis (GLCM) (žiūrėti [8] ir [1]). Klasifikavimui naudojamas palydovinės nuotraukos vaizdas (USGS Earth Explorer). Taip pat sugeneruojami GRF su skirtingais koreliacijos pločiais ir uždedami ant palydovinės nuotraukos. Tokia situacija gali natūraliai susidaryti degant miškui, kai gaisro dūmai uždengia tam tikrą dalį teritorijos. Šie paveiksliukai naudojami klasifikavimo tikslumo tyrimui.

Raktiniai žodžiai: vaizdo klasifikavimas, Gauso atsitiktiniai laukai, klasifikavimas su mokymu, Bajeso diskriminantinė funkcija, klasifikavimas be mokymo, pilkumo lygio pasikartojimų matricos.