SIMILARITY MEASURE BETWEEN VECTOR DATA BASES AND OPTICAL IMAGES FOR CHANGE DETECTION

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1. INTRODUCTION

One of the main fields of application in high resolution remote sensing imagery is cartographic data base updating. In this context, the classical approach consists of detecting objects in images and comparing them to the information stored in the data base. The main drawback of this approach is that pertinent object detection and recognition is a very difficult task. Furthermore, what is usually needed is just an alert for changes in order to conduct a more detailed analysis. In this work, we define a similarity measure between images and cartographic (vector) data bases. This measure is able to perform the comparison between the two sets of data without the need for object or feature extraction.

2. STATISTICAL MODEL

The basic problem addressed in this paper is the detection of changes between an optical image, denoted as $U = \{U_{ij}, i, j = 1, \ldots, n\}$ (where i and j denote the line and column numbers), and a vector data base, denoted as $M = \{M_{ij}, i, j = 1, \ldots, n\}$. The proposed statistical model assumes that the vector data base has been obtained by thresholding an unobserved continuous Gaussian image. More precisely, the value of the pixel M_{ij} is defined as follows

$$M_{ij} = 0 \text{ if } V_{ij} < \theta_3, \text{ and } M_{ij} = 1 \text{ if } V_{ij} > \theta_3,$$

where θ_3 is the threshold and $V = \{V_{ij}, i, j = 1, \ldots, n\}$ is the continuous image (of course, the continuous image as well as the threshold are not available to the user). In order to model correlations between the vector data base U and the optical image V, we assume that the joint distribution of (U_{ij}, V_{ij}) is a bivariate Gaussian distribution with covariance matrix

$$\Sigma = \begin{pmatrix} \text{Var}\, U_{ij} & \text{cov}(U_{ij}, V_{ij}) \\ \text{cov}(V_{ij}, U_{ij}) & \text{Var}\, V_{ij} \end{pmatrix} = \begin{pmatrix} \theta_1^2 & \theta_1\theta_2 \\ \theta_1\theta_2 & 1 \end{pmatrix},$$

and mean vector $(\theta_0, 0)$ (the random variable V_{ij} is assumed to have zero mean and unity variance without loss of generality). As a consequence, the joint distribution of the optical image U_{ij} and the vector data base M_{ij} is characterized by the parameter vector $\boldsymbol{\theta} = (\theta_0, ..., \theta_3)$.

The joint distribution of (U_{ij}, M_{ij}) has been determined in [1] and can be used to determine the correlation coefficient of (U_{ij}, M_{ij}) (that is clearly an interesting feature for change detection)

$$\rho_{ij} = \frac{\text{cov}\,(U_{ij}, M_{ij})}{\sigma\,(U_{ij})\,\sigma\,(M_{ij})} = \frac{\theta_2\,\phi\,(\theta_3)}{\sqrt{F\,(\theta_3)\,[1 - F\,(\theta_3)]}}, \tag{1}$$

where $\phi(x)$ and $F(x)$ are the probability density function and the cumulative distribution function of the $\mathcal{N}(0, 1)$ distribution. Eq. (1) shows that the correlation coefficient ρ_{ij} is related to the coefficients θ_2 and θ_3 of the proposed statistical model. Note that the other parameters θ_0 and θ_1 characterize the marginal distribution of U_{ij} (since $U_{ij} \sim \mathcal{N}(\theta_0, \theta_1^2)$) and are thus less interesting for change detection. The next section addresses the problem of estimating the parameter vector $\boldsymbol{\theta}$ from several measurements of the pair (U_{ij}, M_{ij}). These measurements can be obtained by using pixels belonging to the neighborhood of the current pixel (i, j), defining the so-called estimation window.

3. MAXIMUM LIKELIHOOD METHOD

The maximum likelihood (ML) method consists of estimating the unknown parameter vector $\boldsymbol{\theta}$ by maximizing the joint likelihood of the measurements, or equivalently the log-likelihood. Assuming independence between the different pixels belonging to the estimation window and differentiating the log-likelihood with respect to (wrt) θ_0 and θ_1 leads to the following estimators

$$\widehat{\theta}_0 = \overline{u} = \frac{1}{n^2} \sum_{i,j=1}^{n} u_{ij}, \quad \widehat{\theta}_1^2 = \frac{1}{n^2} \sum_{i,j=1}^{n} (u_{ij} - \overline{u})^2. \tag{2}$$

In other words, the ML estimators of θ_0 and θ_1 are the empirical means and variance of the optical image pixels belonging to the estimation window. This result is easy to understand since the marginal distribution of U_{ij} is the $\mathcal{N}(\theta_0, \theta_1^2)$ distribution. After replacing the parameters

θ_0 and θ_1 by their ML estimates in the log-likelihood, it can be shown (details will be provided in the full paper) that the ML estimates of θ_2 and θ_3 can be obtained by maximizing the following cost function wrt (θ_2, θ_3)

$$A(\theta_2, \theta_3) = \sum_{i,j=1}^{n} (1 - m_{ij}) \log \left[F\left(\frac{\theta_3 - \theta_2 x_{ij}}{R} \right) \right] + \sum_{i,j=1}^{n} m_{ij} \log \left[1 - F\left(\frac{\theta_3 - \theta_2 x_{ij}}{R} \right) \right], \tag{3}$$

under the constraint $-1 \leq \theta_2 \leq 1$ (θ_2 is the correlation coefficient of (U_{ij}, V_{ij})) with $R = \sqrt{1 - \theta_2^2}$ and $x_{ij} = (u_{ij} - \widehat{\theta}_0)/\widehat{\theta}_1$. Note that x_{ij} is obtained by normalizing the optical image U_{ij} using the pixels belonging to the observation window. As a consequence, after appropriate normalization of the optical image, the estimation of θ_2 and θ_3 is decoupled from the estimation of θ_0 and θ_1. The optimization of the cost function (3) wrt (θ_2, θ_3) can be achieved by using a numerical optimization procedure. Simulation results presented in this paper have been obtained by using the Nelder-Mead method [2].

The detection of changes between the vector data base and the optical image can be achieved by using appropriate similarity measures. The strategy advocated in this paper consists of comparing the estimated correlation coefficient to a threshold T_{PFA} depending on the probability of false alarm, i.e, $\widehat{\rho}_{ij} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\lessgtr}} T_{\text{PFA}}$, where $\widehat{\rho}_{ij}$ is obtained from (1) after replacing θ_2 and θ_3 by their ML estimates. The detection performance will be represented through receiver operating characteristics (ROCs) [3, p. 38]. These curves show the probability of detection (P_{D}) (deciding hypothesis H_1 is true when it is actually true) vs. probability of false alarm (P_{FA}) (deciding hypothesis H_1 is true when it is actually not true).

4. SIMULATION RESULTS

Many experiments have been conducted to validate the proposed estimation/detection strategy. The simulations presented in this abstract have been obtained on synthetic data. The first experiment studies the mean square errors (MSEs) of the ML estimates (log scale) for parameters θ_2 and θ_3 for different sizes of the estimation window. The actual parameter vector is $\boldsymbol{\theta} = (0, 1, 0.2, 0)$ for this example (this corresponds to a correlation coefficient $\rho = 0.1542$). All MSEs have been computed using 1000 Monte Carlo runs. The MSEs of the ML estimates are compared with the corresponding Cramer-Rao bounds that can be computed for the proposed statistical model (more details will be provided in the final version of the paper). Fig. 1 shows that the the MSEs of the ML estimator are very close to the Cramer-Rao bounds even for relatively small sample sizes. The second experiment studies ROCs associated to the hypotheses $H_0(\text{no change}) : \rho = \rho_0$ and $H_1(\text{change}) : \rho = \rho_1$, with $\rho_1 = 0.24 < \rho_0 = 0.4$ for different sizes of the observation window. A very good performance can be obtained for windows of size 21×21.

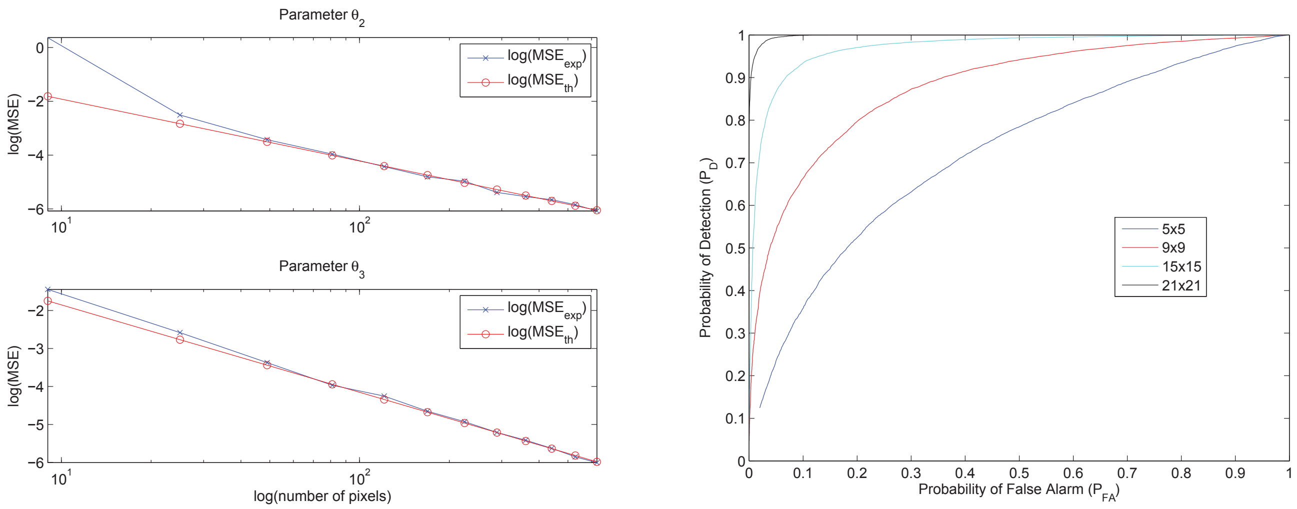

Fig. 1. (left) Estimated MSEs (MSE_{exp}) and Cramér-Rao Bounds (MSE_{th}). (right) ROCs for different window sizes.

5. CONCLUSIONS

This paper studied a statistical model appropriate to vector data bases and continuous Gaussian images. This model was used to estimate an appropriate correlation coefficient between these two kinds of data for change detection. More intensive simulations will be provided in the final version of the paper. In particular, the proposed strategy will be compared with other change detectors, e.g. based on the usual estimator of correlation coefficient. Results obtained with real data sets provided by the CNES will also be included.

6. REFERENCES

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