A Variational Bayesian Approach to Remote Sensing Image Change Detection

Keming Chen[1], Zhenglong Li[1], Jian Cheng[1], Zhixin Zhou[12], Hanqing Lu[1]

[1] National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, Beijing, China, 100190;

[2] Beijing Institute of Remote Sensing, Beijing, China, 100854

E-mail: {kmchen, zlli, jcheng, luhq@nlpr.ia.ac.cn}, zhixin.zhou@ia.ac.cn

ABSTRACT

Change detection is one of the most important applications in the remote sensing society. Usually change detection aims at discerning areas of changes on two registered remote sensing images acquired in the same geographical area at two different times. For such purpose, Maximum Likelihood (ML) estimation of Gaussians Mixture Model (GMM) has been successfully applied to unsupervised change detection. Usually, this estimation is obtained by the Expectation-Maximization (EM) algorithm [1]. In [4], EM is iteratively adopted to perform an unsupervised estimation of the density functions associated with both the changed and unchanged pixels in the difference image. However, without a proper initialization, the EM algorithm may lead to overfitting and poor generalization. Variational Bayesian EM (VBEM) algorithm [2, 3] finds the lower bound of the marginal log-likelihood by assuming a factorized variational distribution on the latent variables and parameters. The VBEM algorithm does not suffer from overfitting and has good generalization capabilities. Moreover it allows for convenient addition of prior information on the parameters [6].

In this paper, we present a variational Bayesian approach to multitemporal remote sensing image change detection. The content of the so called 'difference image' is modeled by finite GMMs, then with the factor analysis techniques, underlying structure of image content is inferred automatically. The proposed method can adaptively determine the number of components in the mixture model. Moreover, to overcome the local optimization problem, a component split strategy is employed in inference process.

Specially, given the difference image $X_D = \{x_i\}_{i=1}^{M*N}$, our goal is to produce a change map $Y = \{y_i \in (\Omega_c, \Omega_n)\}_{i=1}^{M*N}$. In a Bayesian setting, we introduce a *K*-dimension latent variable Z to denote which component the variable x_i belongs to. A variational solution is to approximate $P(Z)$ with a simpler distribution $Q(Z)$ if it can provide a lower bound to the log-likelihood, $\mathcal{L}(X) = ln\, P(X)$. We decompose the $\mathcal{L}(X) = \mathcal{L}(q) + KL(q||p)$, where $KL(q||p)$ is the Kullback-Leibler divergence. Therefore, the optimal approximating distribution Q is equivalent to minimize the Kullback-Leibler divergence $KL(q||p)$. Employing the factorized distributions, we assume that the q distribution factorizes with respect to K disjoint groups, so that $q(Z) = \prod_{i=1}^{K} q_i(Z_i)$. The free-form variational optimization of $\mathcal{L}(q)$ with respect to all of the distribution $q_i(z_i)$ provides the optimal solution:

$$L(q) = \int q_j \ln \tilde{p}(X, Z_j) dZ_j - \int q_j \ln q_j dZ_j + \text{const} \tag{1}$$

Where

$$p(X, Z_j) = \exp\left(\int \ln p(X, Z) \prod_{i \neq j} q_i dZ_i\right) \tag{2}$$

Generalizing the classic Expectation-Maximization (EM) algorithm, the recover $q_j^*(Z_j)$ is performed by iteratively updating Variational Bayes E step (VBE) and Variational Bayes M step (VBM).

Assuming observation x_i generated from a Gaussian distribution, whole observation set X_D is described by GMMs as:

$$p(X \mid Z, u, \Lambda) = \prod_{n=1}^{M*N} \prod_{k=1}^{K} N(x_n \mid u_k, (\Lambda_k)^{-1})^{z_{nk}}, \quad p(Z \mid \pi) = \prod_{n=1}^{M*N} \prod_{k=1}^{K} \pi_k^{z_{nk}} \tag{3}$$

$\Theta = \{\mu, \Lambda, \pi\}$ is the GMM parameters. Considering the conjugate prior:

$$p(\mu \mid \Lambda) = N(\mu_k \mid m_0, (\beta_0, \Lambda_k)^{-1}), \quad p(\Lambda) = W(\Lambda_k \mid W_0, \nu_0) \tag{4}$$

We can formulate our segmentation model as following in a factorized distribution:

$$p(Z \mid X) = p(X, Z, \Theta) = P(X \mid Z, \mu, \Lambda) p(\mu \mid \Lambda) p(\Lambda) p(Z \mid \pi) p(\pi) \tag{5}$$

To maximize the log likelihood, according to the factors $q(Z) = \prod_{i=1}^{K} q_i(Z_i)$ and $q(\Theta^j)$, we have the factor

$$q(Z) \propto \exp\left(\int \ln p(X, Z, \Theta) p(\Theta) d\Theta\right) \tag{6}$$

For each pixel *i*, the distribution of the indicator z_{ik} for each component k is obtained:

$$\ln r_{ik} \propto (\psi(\alpha_k) - \psi(\hat{\alpha})) + \left(\frac{1}{2}\sum_{i=1}^{D} \psi\left(\frac{\nu_k + 1 - i}{2}\right) + D \ln 2 + \ln |W_k|\right) - \frac{1}{2}[D(\beta_k)^{-1} + \nu_k (x_n - m_k)^T W_k (x_n - m_k)] \tag{7}$$

Another critical parameter to the problem of VBEM algorithm is the number of Gaussians, *K*. Considering the generality of the task, we adopt component splitting and component elimination strategies [5]. During the process of optimization, the mixing coefficients of some components π_k may become less than a given threshold θ. As those redundant components have little influence on the lower bound, they are eliminated. On the other way, to prevent getting into the local minimum caused by redundancy removal, a component splitting strategy is developed to introduce new component when it is necessary. The $\mathcal{L}(q(z_k))$ with the largest contribution to the lower bound is chosen to be split into two components. Because of the abilities of component elimination and splitting, VB can determine the suitable component number in the model. In this way, the proposed method can correctly infer the underlying difference image structure without usual sub- or over-segmentation problem which leads to a better change detection results.

To thoroughly assess the validation of the proposed method, we test our approach on two different sets of high resolution optical remote sensing images. *Fig 1* illustrates a sample of change detection result obtained on a set of Ikonos 2m resolution optical images by the proposed approach. In general, the promising performance confirms the effectiveness of the proposed algorithm. The proposed method can correctly infer the underlying image structure without usual sub- or over-segmentation problem.

(a) (b) (c)

Figure 1. Some change detection results produced by our proposed approach.

REFERENCES

[1] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum likelihood from incomplete data via the EM algorithm". J. Royal Stat. Soc., vol. 39, pp. 1-38, 1977.

[2] H. Attias, "Inferring parameters and structure of latent variable models by variational Bayes". In Proc. 15th Conf. Uncertainty in Artificial Intelligence, pp. 21-30, 1999.

[3] M. J. Beal and Z. Ghahramani, "The Variational Bayesian EM Algorithm for Incomplete Data: with Application to Scoring Graphical Model Structures". In Bayesian Statistics, vol. 7, Oxford University Press, pp. 453-464, 2003.

[4] L. Bruzzone and D. F. Prieto, "Automatic analysis of the difference image for unsupervised change detection". IEEE Trans. Geoscience and Remote Sensing, Vol. 38 (3), pp.1171 – 1182, 2000.

[5] Z. Ghahramani and M. J. Beal. "Variational inference for Bayesian mixtures of factor analysers". In Adv. Neu. Inf. Proc. Sys., vol. 12, pp. 449–455, MIT Press, 2000.

[6] Zhenglong Li, Qingshan Liu and Hanqing Lu, "A Variational Inference based Approach for Image Segmentation". Intl. Conf. Pattern Recognition, Florida, Dec. 2008.