MARKOV RANDOM FIELD MODEL-BASED SOIL MOISTURE CONTENT SEGMENTATION FROM MODIS SATELLITE DATA

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1. INTRODUCTION

The soil moisture content plays an important role in hydrology, agronomy, and meteorology. The estimation of soil moisture content is always one of the major issues in the related researches [1–8]. In conventional studies, due to lacking consideration for the non-homogeneity of usage types of the land under research, the spatial variation of soil moisture content couldn't be represented reasonably. It is thus hard to attain the managing and monitoring of water resource. However, recently some researchers have successfully calculated the space-dependent soil moisture content with the aid of optical satellite data, for example, MODIS [3–8]. These researches can be approximately divided into two categories. The first category estimates the values of the soil moisture content [3, 4, 5] and the second category estimates the type of soil moisture content [6, 7, 8]. So far the estimation of the first category is not very accurate, because the land may be partially covered by clouds or vegetations. This paper focuses on the second category. The types to which the soil moisture can belong are few, for example, dryness and wetness. This type information can be used for further applications in hydrology or drought management.

2. THE MODEL

A two-layer statistical model is proposed. The bottom layer is a Markov random field (MRF) that represents the types of soil moisture content. The top layer describes the observations of soil moisture content whose distributions are Gaussians dependent of the underlying MRF realizations. Let *X* denote the MRF and *Z* the top field. At a site *s*, $X_s = x_s$ is the type of the soil moisture content z_s at *s*. The soil moisture content at each site is classified as one of several types, for example, dryness, wetness, and in between. As soon as the types at all the sites are determined, a segmentation of the soil moisture content is obtained. The distribution of MRF *X* is assumed to have the potential functions defined on pair-wise cliques. The potential associated with the clique *c* consisting of two sites *s* and *u*, which are neighbors each other, is described by [9]

$$V_c(x_s, x_u) = \begin{cases} -\beta, & \text{if the } x_s = x_u \\ +\beta, & \text{otherwise} \end{cases},$$

where β controls the trend toward spatial clustering of the same type labels. At a site *s*, given the type $x_s = t,\ t \in \{\text{'wetness', 'dryness', 'in-between'}\}$, the distribution of the soil moisture content z_s is defined by a Gaussian density, $f(z_s \mid x_s = t) = G(\mu_t, \sigma_t)$.

3. SEGMENTATION ALGORITHM

The maximum a posteriori (MAP) segmentation is defined by

$$\hat{x} = \arg\max_x f(x \mid z) = \arg\max_x f(z \mid x) P(x)$$

Considering the prohibitive complexity of direct computing of $P(x)$, an equivalent estimation called iterated conditional modes (ICM) [10] is used. For every site *s*, the ICM is defined by

$$\hat{x}_s = \arg\max_{x_s} f(x_s \mid z, \hat{x}_{\setminus s}),$$

where $\hat{x}_{\backslash s}$ is the available provisional estimate of the type labels at the sites other than s . Assume Z and X are conditionally independent, that is, $f(z \mid x) = \prod_{s} f(z_s \mid x_s)$. We can show that the ICM is equivalent to

$$\hat{x}_s = \arg\max_{x_s} f(z_s \mid x_s) P(x_s \mid \hat{x}_{\backslash s}),$$

where the Gaussian density $f(z_s \mid x_s)$ is as stated before, and the conditional probability $P(x_s \mid \hat{x}_{\backslash s})$ is easy to implement due to the Markovity of the MRF X.

4. PARAMETER ESTIMATION

In this study, soil moisture content was classified into one of the three types, i.e. wetness, dryness, and in-between. A mixture of three Gaussians was adopted to model a given set of soil moisture data [3]. A standard procedure [11] was used to estimate the corresponding parameters: the priors [α_1,α_2,α_3], and the Gaussian parameters [μ_1,μ_2,μ_3,σ_1,σ_2,σ_3]. These parameters were then used to cluster the data into three subsets, which corresponded respectively to the three types of soil moisture content. For each of the subset, a collection of regression coefficients was obtained by fitting the data in the subset [5]. The mean of the Gaussian associated with the type represented by the subset was derived from the regression coefficients. The standard deviations of the Gaussians were estimated respectively from the three subsets of data.

5. SIMULATION AND DISCUSSIONS

The histogram of the soil moisture data [3] looked like multi-humped rather than single-humped. Thus the adoption of Gaussian mixture for the data was appropriate. The ICM segmentation was performed on MODIS satellite data over Taiwan. The segmentation results were quite smooth. The segmentation of soil moisture content will be useful for further applications in hydrological analysis and drought management.

6. REFERENCES

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