Simulated Annealing Techniques in Contextual Fuzzy c-Means Approach for Sub-Pixel Classification

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ABSTRACT

In Bayesian image processing Maximum a Posterior (MAP) Probability is achieved by minimizing the global posterior energy, where the posterior energy is the combination of prior and conditional energy function. In Markov Random Field (MRF) based contextual image classification and restoration process, Simulated Annealing (SA), a stochastic relaxation technique has been used by researchers to establish the MAP solution. For hard classification techniques to establish MRF-MAP solution the SA technique proposed by Metropolis et al. (1953) was used by many researchers, as in the literature it was reported that Metropolis algorithm is easier to program and it performs better in comparison to the Gibbs sampler. In comparison to the traditional hard classifiers, for contextual Fuzzy *c*-Means approach it is more difficult to establish the MAP solution. Since the membership grade for a pixel for all classes should be sum up to 1, at the same time membership values for a single pixel for all the classes need to be updated, it makes the process more complex with compare to the hard classifiers and lastly the infinite number of possible membership values (sampling space), being real numbers between 0 and 1 are the possible values. Sampling from such space is computationally hard.

Therefore the main objective of this study is to establish suitable sampler to estimate the MAP solution for contextual FCM approach. The Metropolis algorithm, which randomly generates new membership image configuration and calculates the energy function associated with the new image configuration, was used initially for contextual FCM approach. From the experiments it was found that, while ignoring the smoothness prior (contextual) information the contextual FCM solution is not identical to the FCM solution. The Metropolis algorithm was tested on AWiFS image of IRS P6 satellite and the results are shown in Fig 1:

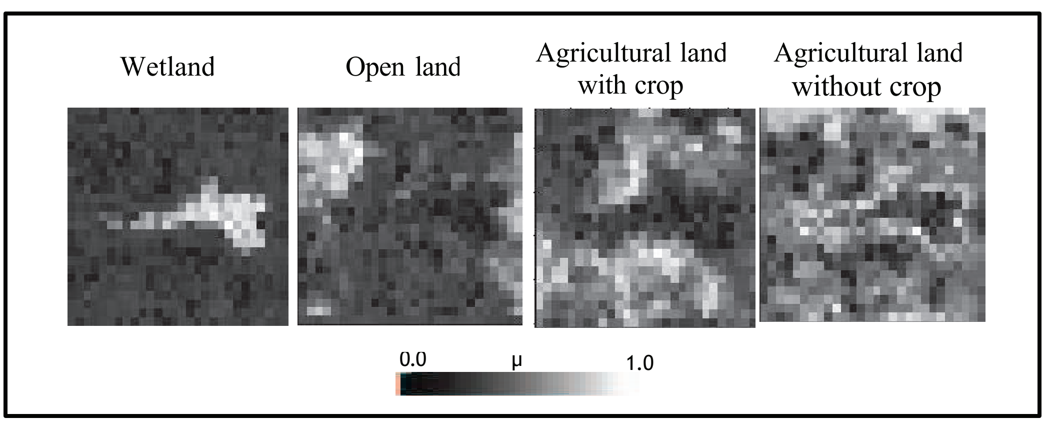

Fig. 1 Fraction images of contextual FCM classification (Metropolis) for AWiFS data

To quantify the overall difference between FCM and MRF-FCM solution (Fig. 1) the RMSE value was calculated and quite high RMSE value (0.2323) has been found. Therefore it indicates that Metropolis algorithm is unable to sample efficiently for fuzzy membership grades.

Afterwards the SA algorithm proposed by Geman and Geman, known as Gibbs sampler, was used in order to establish the MAP. Gibbs sampler generates new membership values for each pixel, based on the local conditional distribution and it also includes the temperature parameter. The concept of Gibbs sampler is similar to the concept of Metropolis algorithm the only difference is how the next configuration is generated. The Gibbs sampler was applied on the same image and it was found that while ignoring smoothness prior information the contextual FCM solution is identical to the FCM solution. Moreover for Gibbs sampler, the convergence of MAP solution was ten times faster than the Metropolis algorithm. The experimental results of Gibbs sampler are shown in Fig. 2.

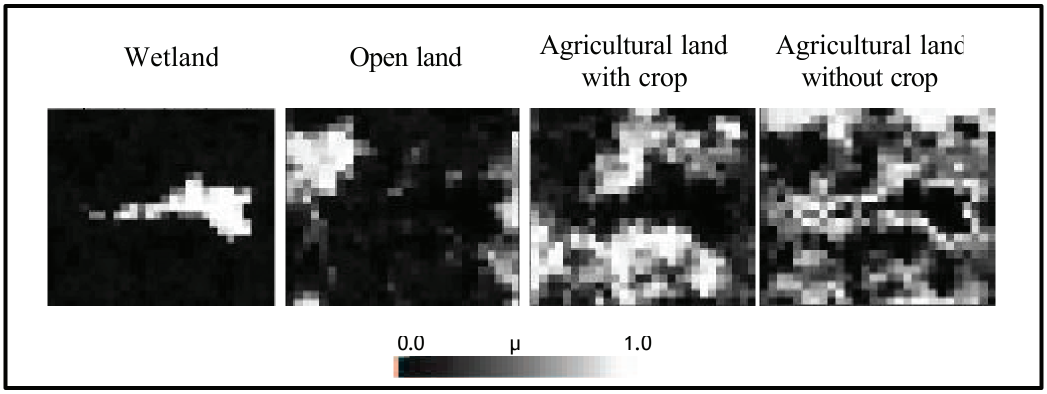

Fig. 2 Fraction images of contextual FCM classification (Gibbs) for AWiFS data

The RMSE value with standard FCM solution was found very low (0.00013), which indicates good closeness to the FCM solution. Therefore from the above study it can be concluded that for a soft classifier Gibbs sampler is more suitable to model the posterior probability in comparison to the Metropolis algorithm.

Keywords: Maximum a Posterior, Markov Random Field, context, Fuzzy *c*-Means, Simulated Annealing, Metropolis algorithm, Gibbs sampler.

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