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Markov Random Fields for SAR Remote Sensing Applications

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Abstract—This article aims at illustrating the powerfulness of Bayesian and specially Markovian frameworks for different remote sensing applications and in particular for SAR (Synthetic Aperture Radar) image processing. Indeed, the Markovian model is a very convenient way to introduce prior knowledge on the problem to solve. It will first be evoked with examples on the pixel level like filtering, segmentation and classification. Then higher level applications, like object recognition, and global image interpretation will be developed.

1. INTRODUCTION

There are nowadays more and more remote sensing data available, either optic or radar images. These huge amounts of data make necessary the development of automatic tools to process the images and help the final user to take the "best" decision. A well adapted framework is the Bayesian one, which permits to introduce as much knowledge as possible in the decision process and in the frame of a probabilistic world. In particular, Markov models are able to describe spatial relationships between the grey-levels or labels of the considered features. Therefore, they are a powerful tool to introduce adapted prior on the problem to solve, either for low-level applications (this fact is rather well-known), but as we sill see, also for higher level ones.

We illustrate this property and the generality of Markovian methods on two kinds of examples. First, we deal with examples at the pixel level. Then, in a second part, we show that Markov random fields provide also efficient models for higher level purposes like object detection and image interpretation. The described methods are illustrated with examples on SAR images. These ones are obtained with coherent illumination and present a noisy appearance due to speckle phenomenon which causes specific difficulties for automatic processes.

2. PIXEL-BASED APPLICATIONS

Markov random fields are widely used and since a long time for low-level applications like filtering (denoising), segmentation and classification. Due to the previously mentioned speckle, SAR images are rather difficult to interpret. To reduce this perturbation, many "filters" have been proposed. The prior on the searched for solution can be exploited in different ways: to introduce a specific punctual distribution, to impose some regularity using the relationship between a pixel and its neighbors, or to introduce many possible models for the solution. For the two last cases, Markovian framework provides well adapted tools. Indeed, the Markovian model permits to take edges into account inside a coherent framework (instead of adding a separate detection). This can be done using either an explicit boundary model or appropriate regularization functions. But this model is limited since it supposes homogeneous areas separated by edges. An improved filter allows many contextual models (Gauss Markov random fields) [1], which correspond to many possible textures of the underlying scene.

Markovian models are also widely used for segmentation and classification. In this case, the searched for solution is a labelled image. Bayesian techniques with a supervised learning are frequently used, specially for polarimetric data. One of the main difficulties with this model is the weighting between the data attachment term and the regularization one. Therefore unsupervised methods of estimation have been proposed. A fully unsupervised framework is described in [2]. The distributions are constrained to be in the Pearson system, but their parameters and the prior parameters are automatically learnt during the process. Both Markov fields and chains are tested and compared. One of the main drawbacks, specially with the Markov fields, is the computing time since many realizations must be sampled.

3. HIGHER-LEVEL APPLICATIONS

The Bayesian and specially Markovian methods have also a great potential for higher level purposes. Using features like regions or segments or any particular feature of interest, the whole Markovian framework can be applied to introduce contextual knowledge on the searched for solution. We will illustrate this property with two examples.

3.1. Road detection

In this application, the objects of interest are the roads and we have a huge prior knowledge about their shape: they are long and they have a quite low curvature except for cross-roads. Although the Markovian model can be applied at the pixel level [3], in this context the appropriate features to deal with are the segments. Then the prior knowledge on the shape of the roads can be introduced using a segment graph [4]. Because only a local knowledge on the segment scale is necessary, the Markovian assumption is verified for an appropriate neighborhood. Starting from a set of detected segments and considering almost all the connections between them to build the graph, the use of simple clique potentials permits to recover the network and suppress the falsely detected segments.

Besides, the flexibility of the framework allows to define different types of networks just by changing the clique potentials. For instance, the information that cross-roads are frequent can be introduced for dealing with dense urban areas. In the case of river detection, different scales must be taken into account, and also the sinuous shapes of the objects.

3.2. Image interpretation

Another example to illustrate the Markovian model potential, is the use of a Markov random field defined on a graph of regions to make the global interpretation of a SAR image [5]. As before, it permits to introduce spatial coherence in the process defining the relationships between the interest classes (urban areas, forests, roads,...). In this application, starting from a set of detected regions (obtained for instance by an over-segmentation of the image), the labelling of the scene is made using clique potentials reflecting our prior knowledge on the scene organization (for example, the fact that roads are frequent inside urban areas, and very rare in water areas). Examples for different SAR images will be presented.

4. CONCLUSION

Bayesian and Markovian methods are powerful frameworks for a wide variety of remote sensing applications. They can be used in many ways with more or less prior information. But we believe that improved results can be obtained using adapted prior knowledge. Two main problems to introduce this information in a Markovian framework have to be solved. The first one is the clique potential definition. The potentials can be defined in a supervised way for simple cases [4], but an automatic learning should improve the results and is necessary for more complicated cases. Therefore the automatic learning of the clique potentials is a real challenge. If solutions exist for the parameters of the clique potentials in some simple cases [2], the direct learning of all the clique potentials, specially for higher level applications, is still a difficult task. Neural networks for instance can provide some solutions [6]. The second problem is the building of the graph specially for object detection like road networks. A promising perspective in this domain is the stochastic geometry which permits to modify randomly the site graph [7].

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