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Review on Markov Random Field (Mrf) in Video Surveillance

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I. Introduction

Markov random field models have become useful in several areas of image processing. The success of MRFs can be attributed to the fact that they give rise to good, flexible, stochastic image models. The goal of image modeling is to find a suitable representation of the intensity distribution of a given image. What is adequate often depends on the task at hand and MRF image models have been versatile enough to be applied in the areas of image and texture synthesis, image compression, restoration, texture classification, and surface reconstruction. Tomographic reconstruction, image and texture segmentation. Our aim is to highlight the central ideas of this field using illustrative examples and provide pointers to the many applications.

A guiding insight underlying most of the work on MRFs in image processing is that the information enclosed in the local, physical structure of images is sufficient to obtain a good, global image representation. This notion is captured by means of local, conditional probability distribution. Here, the image intensity at a particular location depends only on a neighborhood of pixels.

The conditional distribution is called an MRF. For example, a typical MRF model assumes that the image is locally smooth except for relatively few intensity gradient discontinuities corresponding to region boundaries or edges. The MRF image models are defined on the image intensities and on a further set of hidden attributes (edges, texture and region labels). The observed quantities are usually noisy, blurred images, feature vectors or projectiondata in the case of emission tomography. The intensity image underlying the observations is needed in applications like restoration and tomographic reconstruction, whereas, region, boundary and texture labels are sought in applications like texture segmentation.

Once the local, conditional probability distribution of the MRF is specified, there are five remaining steps involved. First, the joint distribution of the MRF is obtained. In this way, the image is represented in one global, joint probability distribution. Next, the process by which the observations are generated from the image is captured in a degradation probability distribution. Then, Bayes' theorem is invoked to obtain the posterior probability distribution of the image given the observations. The posterior distribution gives us the probability that an image (with smooth regions and sharp region boundaries) could have been degraded to obtain the particular observed noisy, blurred image. Finally, since the MRFs are specified with model parameters, these are estimated from a training set (if one exists) or adaptively along with the cost minimization phase alluded to earlier. The overall MRF framework fits well within Bayesian estimation.

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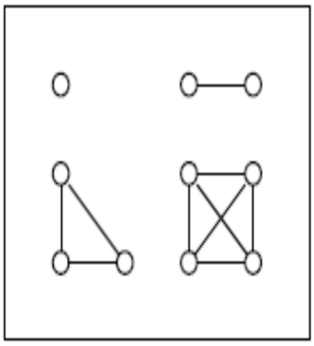
II. FRAME WORK FOR ESTIMATION AND INFERENCE

As mentioned in the introduction, MRF image models represent knowledge in terms of “local” probability distributions. Specifically, the kinds of probability distributions generated by MRFs have a local neighborhood structure. Neighborhood systems commonly used by MRFs are depicted in below figure.



(a)

			6			
	5	4	3	4	5	
	4	2	1	2	4	
6	3	1	s	3	3	6
	4	2	1	2	4	
	5	4	3	4	5	
			6			

(b)

Figure 1: Neighborhood systems commonly used by MRFs.

Let us associate an image with a random process X whose element is Xs, where s Є S refers to a site in the image.

$$\Pr(X_s = x_s | X_t = x_t, t \neq s, t \in S) = \Pr(X_s = x_s | X_t = x_t, t \in G_s).$$

Where X and x denote the random field and a particular realization respectively and G is the local neighborhood in keeping with the spirit of MRF modeling. The MRF model consists of a set of cliques. A clique is a collection of sites such that any two sites are neighbors. Different orders of cliques are shown in figure 1 (a). The order of a clique refers to the number of distinct sites that appear multiplicatively. We now calculate the clique energies involving the site by expanding the conditional probability density and collecting the terms. There are cliques of order one and two. They are

$$\frac{x_{ij}^2}{2}, \quad -\frac{x_{ij}x_{i,j+1}}{4}, \quad \text{and} \quad -\frac{x_{ij}x_{i+1,j}}{4}.$$

The first term in above equation is order one and the latter two terms are of order two.

III. MRF- GIBBS EQUIVALENCE

Gibbs field is a representation of a set of random variables and their relationships. An example of a Gibbs Field is given in figure 2 edges are undirected, and connote some correlation between the connected nodes.

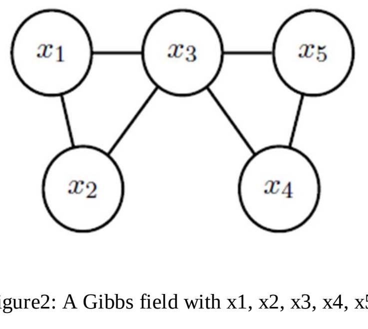


Figure2: A Gibbs field with x1, x2, x3, x4, x5

As with a Bayes’ Net, fewer connections mean more structure. Gibbs field are more powerful because they imply a way to write the joint probability of the random variables as functions over cliques in graph.

MRF and Gibbs fields both "look" the same in the sense that they are undirected graphs. Gibbs fields have an implicit probability function for each clique, while MRFs only specify the conditional independence. A natural question to ask is whether we can use the same graph that represents an MRF and same distributions. The Hamersley-Clifford theorem (also called the fundamental theorem of random fields) proves that a Markov Random field and Gibbs Field are equivalent with regard to the same graph. In other words:

- Given any Markov Random field, all joint probability distributions that satisfies the conditional independence relationship specified by the corresponding field.
- Given any Gibbs field, all of its joint probability distributions satisfy the conditional independence relationships specified by the corresponding independence relationships specified by the corresponding Markov Random field.

IV. MAP ESTIMATION

Restricting our focus to MAP estimation, we observe that MAP estimation reduces to minimizing the posterior energy function E(x). This minimization involves the different kinds of processes which make up X. For example, in edge preserving image restoration the process X includes both continuous image intensities and binary valued edge variables.

Consequently, the minimization of the posterior objective function is a difficult problem due to the presence of non-trivial local minima. A general technique for finding global minima is Simulated Annealing (SA) but it is usually computationally very intensive. Recently, a lot of effort has been expended in obtaining good sub-optimal solutions to the MAP estimation problem.

Deterministic Annealing (DA) is a general method that has emerged recently. Deterministic annealing methods begin with a modified posterior.

$$\Pr(X = x | Y = y) = \frac{1}{Z(\beta)} \exp(-\beta E(x))$$

Where $\beta > 0$ is the inverse temperature. Note that the partition function is now a function of the inverse temperature. The terminology is inherited from statistical physics.

The parameters are now estimated by maximizing the product of the conditional distributions at each site. The availability of a suitable training set is critical to both likelihood and pseudo-likelihood parameter estimation. When training set is not available, parameter estimation. When a training set is not available, parameters estimation and cost minimization proceed in lockstep.

V. CONCLUSION

In sum, the MRF framework is well suited to a wide variety of image processing problems. Our exposition has been brief and we have ignored important issues like validation, choice of the order of MRF models and size of training sets. MRF models being parametric, introduce a certain kind of basis into the image representation. This seems to be the right kind of bias for tasks like image restoration, tomographic reconstruction and texture segmentation. However, if the order of the chosen models is incorrect, high bias could result.

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