Introduction to Probabilistic Image Processing and Bayesian Networks

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Markov Random Fields for Image Processing

Markov Random Fields are One of Probabilistic Methods for Image processing.


Markov Random Fields for Image Processing

In Markov Random Fields, we have to consider not only the states with high probabilities but also ones with low probabilities.

In Markov Random Fields, we have to estimate not only the image but also hyperparameters in the probabilistic model.

We have to perform the calculations of statistical quantities repeatedly.

We need a deterministic algorithm for calculating statistical quantities. Belief Propagation
Belief Propagation has been proposed in order to achieve probabilistic inference systems (Pearl, 1988).

It has been suggested that Belief Propagation has a closed relationship to Mean Field Methods in the statistical mechanics (Kabashima and Saad 1998).

Generalized Belief Propagation has been proposed based on Advanced Mean Field Methods (Yedidia, Freeman and Weiss, 2000).

Interpretation of Generalized Belief Propagation also has been presented in terms of Information Geometry (Ikeda, T. Tanaka and Amari, 2004).
Probabilistic Model and Belief Propagation

Function consisting of a product of functions with two variables can be assigned to a graph representation.

\[ \sum \sum \sum \sum \sum A(x_1, x_2)B(x_3, x_2)C(x_4, x_2)C(x_5, x_2) \]

\[ \sum \sum \sum A(x_1, x_2)B(x_2, x_3)C(x_3, x_1) \]

Examples

Belief Propagation can give us an exact result for the calculations of statistical quantities of probabilistic models with tree graph representations.

Generally, Belief Propagation cannot give us an exact result for the calculations of statistical quantities of probabilistic models with cycle graph representations.
Applications of belief propagation to many problems which are formulated as probabilistic models with cycle graph representations have caused to many successful results.

- Probabilistic Inference in AI (Kappen and Wiegerinck, NIPS, 2002).
Purpose of My Talk

- Review of formulation of probabilistic model for image processing by means of conventional statistical schemes.
- Review of probabilistic image processing by using Gaussian graphical model (Gaussian Markov Random Fields) as the most basic example.
- Review of how to construct a belief propagation algorithm for image processing.
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Image Representation in Computer Vision

Digital image is defined on the set of points arranged on a square lattice.
The elements of such a digital array are called pixels.
We have to treat more than 100,000 pixels even in the digital cameras and the mobile phones.

\[ \begin{align*}
\text{Image Dimensions: } & 640 \times 480 = 307,200 \text{ Pixels} \\
\end{align*} \]
At each point, the intensity of light is represented as an integer number or a real number in the digital image data. A monochrome digital image is then expressed as a two-dimensional light intensity function and the value is proportional to the brightness of the image at the pixel.
Noise Reduction by Conventional Filters

The function of a linear filter is to take the sum of the product of the mask coefficients and the intensities of the pixels.

Smoothing Filters

\[
\begin{bmatrix}
192 & 202 & 190 \\
202 & 219 & 120 \\
100 & 218 & 110 \\
\end{bmatrix}
\]

Average = \[
\begin{bmatrix}
192 & 202 & 190 \\
202 & 219 & 120 \\
100 & 218 & 110 \\
\end{bmatrix}
\] = 173

It is expected that probabilistic algorithms for image processing can be constructed from such aspects in the conventional signal processing.

Markov Random Fields

Algorithm

Probabilistic Image Processing

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Bayes Formula and Bayesian Network

\[
\Pr\{A \mid B\} = \frac{\Pr\{B \mid A\} \Pr\{A\}}{\Pr\{B\}}
\]

The Bayes formula can be applied to the estimation of the original information from the given data.

Event \(A\) is given as the observed data. Event \(B\) corresponds to the original information to estimate. Thus the Bayes formula can be applied to the estimation of the original information from the given data.
Image Restoration by Probabilistic Model

Assumption 1: The degraded image is randomly generated from the original image by according to the degradation process.

Assumption 2: The original image is randomly generated by according to the prior probability.

\[ \text{Bayes Formula} \]

\[ \text{Posterior} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Marginal Likelihood}} \]

\[ \Pr\{\text{Original Image} | \text{Degraded Image}\} = \frac{\Pr\{\text{Degraded Image} | \text{Original Image}\} \times \Pr\{\text{Original Image}\}}{\Pr\{\text{Degraded Image}\}} \]
The original images and degraded images are represented by $f = \{f_i\}$ and $g = \{g_i\}$, respectively.

- $f_i$: Light Intensity of Pixel $i$ in Original Image
- $g_i$: Light Intensity of Pixel $i$ in Degraded Image

Position Vector of Pixel $i$: $\vec{r}_i = (x_i, y_i)$
Probabilistic Modeling of Image Restoration

Assumption 1: A given degraded image is obtained from the original image by changing the state of each pixel to another state by the same probability, independently of the other pixels.

\[
\Pr\{\text{Degraded Image } g \mid \text{Original Image } f\} = \Pr\{G = g \mid F = f\} = \prod_{i=1}^{N} \Psi(g_i, f_i)
\]
Assumption 2: The original image is generated according to a prior probability. Prior Probability consists of a product of functions defined on the neighbouring pixels.
Prior Probability for Binary Image

It is important how we should assume the function $\Phi(f_i, f_j)$ in the prior probability.

$$\Pr\{F = f\} = \prod_{i, j: \text{Nearest Neighbour}} \Phi(f_i, f_j)$$

We assume that every nearest-neighbour pair of pixels take the same state of each other in the prior probability.

$$\Phi(1,1) = \Phi(0,0) > \Phi(0,1) = \Phi(1,0)$$

Probability of Neighbouring Pixel

$$\begin{align*}
\Phi(i, j) &= p \\
\Phi(i, j)^\prime &= 1 - p
\end{align*}$$
Prior Probability for Binary Image

Prior probability prefers to the configuration with the least number of red lines.

Which state should the center pixel be taken when the states of neighbouring pixels are fixed to the white states?

Probability of Nearest Neighbour Pair of Pixels
Prior Probability for Binary Image

Which state should the center pixel be taken when the states of neighbouring pixels are fixed as this figure?

Prior probability prefers to the configuration with the least number of red lines.
What happens for the case of large number of pixels?

Covariance between the nearest neighbour pairs of pixels

Patterns with both ordered states and disordered states are often generated near the critical point.

Disordered State

Critical Point (Large fluctuation)

Ordered State

Sampling by Markov chain Monte Carlo

\[ p \]

Small \( p \) vs. Large \( p \)
Pattern near Critical Point of Prior Probability

Covariance between the nearest neighbour pairs of pixels

We regard that patterns generated near the critical point are similar to the local patterns in real world images.

small $p$ \quad ln $p$ \quad large $p$

similar
Bayesian Image Analysis

Original Image $\Pr\{F = f\} \rightarrow f$

Degradation Process $\Pr\{G = g | F = f\} \rightarrow g$

Prior Probability

Degraded Image

Posterior Probability

$\Pr\{F = f | G = g\} = \frac{\Pr\{G = g | F = f\} \Pr\{F = f\}}{\Pr\{G = g\}}$

$\Omega$ : Set of all the pixels

$B$ : Set of all the nearest neighbour pairs of pixels

Image processing is reduced to calculations of averages, variances and co-variances in the posterior probability.
Estimation of Original Image

We have some choices to estimate the restored image from posterior probability.
In each choice, the computational time is generally exponential order of the number of pixels.

(1) $\hat{f} = \arg \max_z \Pr\{F = z \mid G = g\}$  

Maximum A Posteriori (MAP) estimation

(2) $\hat{f}_i = \arg \max_{z_i} \Pr\{F_i = z_i \mid G = g\}$  

Maximum posterior marginal (MPM) estimation

$$\Pr\{F_i = f_i \mid G = g\} = \sum_{f \setminus f_i} \Pr\{F = f \mid G = g\}$$

(3) $\hat{f}_i = \arg \min_{\xi_i} \left( \xi_i - \sum_z z_i \Pr\{F = z \mid G = g\} \right)^2$  

Thresholded Posterior Mean (TPM) estimation
Statistical Estimation of Hyperparameters

Hyperparameters $\alpha$, $\beta$ are determined so as to maximize the marginal likelihood $\Pr\{G=g|\alpha,\beta\}$ with respect to $\alpha$, $\beta$.

\[
(\hat{\alpha}, \hat{\beta}) = \arg \max_{(\alpha, \beta)} \Pr\{G = g | \alpha, \beta\}
\]

\[
\Pr\{G = g | \alpha, \beta\} = \sum_{z} \Pr\{G = g | F = z, \beta\} \Pr\{F = z | \alpha\}
\]

Original Image

Marginalized with respect to $F$

Degraded Image

Marginal Likelihood
Maximization of Marginal Likelihood by EM Algorithm

**Marginal Likelihood**

\[
Pr\{G = g \mid \alpha, \sigma\} = \sum_z Pr\{G = g \mid F = z, \sigma\} Pr\{F = z \mid \alpha\}
\]

**Q-Function**

\[
Q(\alpha, \sigma \mid \alpha', \sigma', g) = \sum_z Pr\{F = z \mid G = g, \alpha', \sigma'\} \ln Pr\{F = z, G = g \mid \alpha, \sigma\}
\]

**EM (Expectation Maximization) Algorithm**

E-step and M-Step are iterated until convergence:

**E - Step :**

\[
Q(\alpha, \sigma \mid \alpha(t), \sigma(t)) \leftarrow \sum_z Pr\{F = z \mid G = g, \alpha(t), \sigma(t)\} \ln Pr\{F = z, G = g \mid \alpha, \sigma\}
\]

**M - Step :**

\[
(\alpha(t + 1), \sigma(t + 1)) \leftarrow \arg \max_{(\alpha, \sigma)} Q(\alpha, \sigma \mid \alpha(t), \sigma(t))
\]
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Bayesian Image Analysis by Gaussian Graphical Model

Prior Probability

\[ \Pr\{F = f\} \propto \exp\left(-\frac{1}{2} \alpha \sum_{ij \in B} (f_i - f_j)^2\right) \]

Patterns are generated by MCMC.

\( f_i \in (-\infty, +\infty) \)

\( \Omega \): Set of all the pixels

\( B \): Set of all the nearest-neighbour pairs of pixels

\( \alpha = 0.0001 \)

\( \alpha = 0.0005 \)

\( \alpha = 0.0030 \)

Markov Chain Monte Carlo Method
Bayesian Image Analysis by Gaussian Graphical Model

Degradation Process is assumed to be the additive white Gaussian noise.

\[
\Pr \{ G = g | F = f \} = \prod_{i \in \Omega} \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left( -\frac{1}{2\sigma^2} (f_i - g_i)^2 \right)
\]

\( \Omega \): Set of all the pixels

Degraded image is obtained by adding a white Gaussian noise to the original image.

\[
g_i - f_i \sim N(0, \sigma^2)
\]

Histogram of Gaussian Random Numbers
Bayesian Image Analysis by Gaussian Graphical Model

Posterior Probability

\[ P(f \mid g, \alpha, \sigma) \propto \exp \left( -\frac{1}{2\sigma^2} \sum_{i \in \Omega} (f_i - g_i)^2 - \frac{1}{2} \alpha \sum_{ij \in B} (f_i - f_j)^2 \right) \]

Average of the posterior probability can be calculated by using the multi-dimensional Gauss integral Formula

\[ \int zP(z \mid g, \alpha, \sigma)dz = \frac{I}{I + \alpha \sigma^2 C} g \]

\[ \langle i \mid C \mid j \rangle = \begin{cases} 4 & (i = j) \\ -1 & (ij \in B) \\ 0 & \text{(otherwise)} \end{cases} \]

Multi-Dimensional Gaussian Integral Formula
Bayesian Image Analysis by Gaussian Graphical Model

Iteration Procedure of EM algorithm in Gaussian Graphical Model

\[
\alpha(t) \leftarrow \left( \frac{1}{N} \text{Tr} \left( \frac{\sigma(t-1)^2 C}{I + \alpha(t-1)\sigma(t-1)^2 C} \right) + \frac{1}{N} g^T g \right)^{-1} \frac{C}{I + \alpha(t-1)\sigma(t-1)^2 C}
\]

\[
\sigma(t) \leftarrow \sqrt{\frac{1}{N} \text{Tr} \left( \frac{\sigma(t-1)^2 I}{I + \alpha(t-1)\sigma(t-1)^2 C} \right) + \frac{1}{N} g^T g \left( \frac{\alpha(t-1)^2 \sigma(t-1)^4 C^2}{I + \alpha(t-1)\sigma(t-1)^2 C} \right) g}
\]

\[
m(t) = \frac{I}{I + \alpha(t)\sigma(t)^2 C}
\]

\[
\hat{f}_i(t) = \arg \min_{z_i} (z_i - m_i(t))^2
\]

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Image Restoration by Markov Random Field Model and Conventional Filters

<table>
<thead>
<tr>
<th>Statistical Method</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowpass Filter</td>
<td></td>
</tr>
<tr>
<td>(3x3)</td>
<td>388</td>
</tr>
<tr>
<td>(5x5)</td>
<td>413</td>
</tr>
<tr>
<td>Median Filter</td>
<td></td>
</tr>
<tr>
<td>(3x3)</td>
<td>486</td>
</tr>
<tr>
<td>(5x5)</td>
<td>445</td>
</tr>
</tbody>
</table>

\[
MSE = \frac{1}{|\Omega|} \sum_{i \in \Omega} (f_i - \hat{f}_i)
\]

\(\Omega\): Set of all the pixels

Original Image | Degraded Image
---|---
![Original Image](image1.png) | ![Degraded Image](image2.png)

Restored Image

- MRF
- (3x3) Lowpass
- (5x5) Median
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Graphical Representation for Tractable Models

Tractable Model

\[
\sum_{A=1,F} \sum_{B=1,F} \sum_{C=1,F} f(A,D) g(B,D) h(C,D)
\]

\[
= \left( \sum_{A=1,F} f(A,D) \right) \left( \sum_{B=1,F} g(B,D) \right) \left( \sum_{C=1,F} h(C,D) \right)
\]

It is possible to calculate each summation independently.

Intractable Model

\[
\sum_{A=1,F} \sum_{B=1,F} \sum_{C=1,F} f(A,B) g(B,C) h(C,A)
\]

It is hard to calculate each summation independently.
Belief Propagation for Tree Graphical Model

After taking the summations over red nodes 3, 4 and 5, the function of nodes 1 and 2 can be expressed in terms of some messages.

\[
\sum_{f_3} \sum_{f_4} \sum_{f_5} A(f_1, f_2)B(f_2, f_3)C(f_2, f_4)D(f_2, f_5)
\]

\[
= \left( \sum_{f_3} B(f_2, f_3) \right) \left( \sum_{f_7} C(f_2, f_4) \right) \left( \sum_{f_8} D(f_2, f_5) \right)
\]

\[
M_{3 \rightarrow 2}(f_2) \quad M_{4 \rightarrow 2}(f_2) \quad M_{5 \rightarrow 2}(f_2)
\]
Belief Propagation for Tree Graphical Model

By taking the summation over all the nodes except node 1, message from node 2 to node 1 can be expressed in terms of all the messages incoming to node 2 except the own message.

\[ \sum_{\mathbb{Z}_2} M_{2\rightarrow 1} = M_{3\rightarrow 2} \cdot M_{4\rightarrow 2} \cdot M_{5\rightarrow 2} \]

Summation over all the nodes except 1
Loopy Belief Propagation for Graphical Model in Image Processing

Graphical model for image processing is represented in terms of the square lattice. Square lattice includes a lot of cycles. Belief propagation are applied to the calculation of statistical quantities as an approximate algorithm.

Every graph consisting of a pixel and its four neighbouring pixels can be regarded as a tree graph.
Loopy Belief Propagation for Graphical Model in Image Processing

Message Passing Rule in Loopy Belief Propagation

Averages, variances and covariances of the graphical model are expressed in terms of messages.

$$\sum \Phi_{12}(z_1, f_2) M_{3 \rightarrow 1}(z_1) M_{4 \rightarrow 1}(z_1) M_{5 \rightarrow 1}(z_1)$$

$$\sum_{z_1} \sum_{z_2} \Phi_{12}(z_1, z_2) M_{3 \rightarrow 1}(z_1) M_{4 \rightarrow 1}(z_1) M_{5 \rightarrow 1}(z_1)$$
Loopy Belief Propagation for Graphical Model in Image Processing

Each massage passing rule includes 3 incoming messages and 1 outgoing message.

We have four kinds of message passing rules for each pixel.

Visualizations of Passing Messages
EM algorithm by means of Belief Propagation

EM Algorithm for Hyperparameter Estimation

\[(\alpha(t + 1), \sigma(t + 1))\]
\[\leftarrow \arg \max_{(\alpha, \sigma)} Q(\alpha, \sigma | \alpha(t), \sigma(t), g)\]

Update Rule of Loopy BP

\[M_{2 \rightarrow 1} = \sum_{z_2} M_{3 \rightarrow 2} M_{4 \rightarrow 2} M_{5 \rightarrow 2}\]
Probabilistic Image Processing by EM Algorithm and Loopy BP for Gaussian Graphical Model

\[
(\alpha(t + 1), \sigma(t + 1)) \leftarrow \arg \max_{(\alpha, \sigma)} Q(\alpha, \sigma | \alpha(t), \sigma(t), g)
\]

\[
\hat{\alpha}_{\text{Exact}} = 37.624, \quad \hat{\sigma}_{\text{Exact}} = 0.000713
\]

\[
\hat{\alpha}_{\text{LBP}} = 36.335, \quad \hat{\sigma}_{\text{LBP}} = 0.000600
\]

MSE:315

MSE:327

Loopy Belief Propagation

Exact
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Digital Images Inpainting based on MRF

**Markov Random Fields**

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Summary

- Formulation of probabilistic model for image processing by means of conventional statistical schemes has been summarized.

- Probabilistic image processing by using Gaussian graphical model has been shown as the most basic example.

- It has been explained how to construct a belief propagation algorithm for image processing.
Statistical Mechanics Informatics for Probabilistic Image Processing

Original ideas of some techniques, Simulated Annealing, Mean Field Methods and Belief Propagation, is often based on the statistical mechanics.

  Image Processing for Markov Random Fields (MRF)
  (Simulated Annealing, Line Fields)

  Image Processing in EM algorithm for Markov Random
  Fields (MRF) (Mean Field Methods)

  Cluster Variation Method for MRF in Image Processing

Mathematical structure of Belief Propagation is equivalent to Bethe Approximation and Cluster Variation Method (Kikuchi Method) which are ones of advanced mean field methods in the statistical mechanics.
It has been suggested that statistical performance estimations for probabilistic information processing are closed to the spin glass theory.

The computational techniques of spin glass theory has been applied to many problems in computer sciences.

- CDMA Multiuser Detection in Mobile Phone Communication (T. Tanaka: IEEE Information Theory, 2002).
SMAPIP Project

Member:
K. Tanaka, Y. Kabashima,
H. Nishimori, T. Tanaka,
M. Okada, O. Watanabe,
N. Murata, .......

Webpage URL: http://www.smapip.eei.metro-u.ac.jp/

Period: 2002 – 2005

Head Investigator: Kazuyuki Tanaka

MEXT Grant-in Aid for Scientific Research on Priority Areas
DEX-SMI Project

Deepening and Expansion of Statistical Mechanical Informatics

MEXT Grant-in Aid for Scientific Research on Priority Areas

Period: 2006 – 2009

Head Investigator: Yoshiyuki Kabashima

http://dex-smi.sp.dis.titech.ac.jp/DEX-SMI/
References
