# 1996 IEEE Computer Society Conference on Computer Vision and Pattern Recognition
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Proceedings

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# Chairs' Introduction to the CVPR'96 Proceedings

This proceedings contains the papers presented at the 1996 Conference on Computer Vision and Pattern Recognition, held June 18-20, 1996 in San Francisco, California. This is the fifteenth time this conference has been held since 1977.

This year 551 papers were submitted, a new record, representing the latest creative work of researchers from around the world. From these papers, 137 were accepted for the technical program: 73 for oral presentation and 64 for poster presentation. We do not make any distinction in terms of quality between oral and poster presentation.

In order to fairly review such a large number of papers, the program committee was increased in size this year to 50 highly respected members of the community, including about half of whom had never served on the program committee before. In order to improve the evaluation process, each paper was sent to three, not the usual two, members of the program committee. The papers were then reviewed by the program committee members, with the possible help of people in their local group. All reviews were "double-blind." We wish to thank the members of the program committee for their time and expertise in carefully evaluating so many papers.

In January 1996, the General Chair, two Program Chairs and a program subcommittee, met in San Francisco to select the papers. To facilitate this process, the papers were divided into eight broad areas, with two or three people at the meeting assigned to each area. Each area read the reviews of all the papers in that area, and then discussed and evaluated their papers. The top papers from all the areas were then compared and a final set of papers selected. Paper authors remained anonymous throughout this meeting and we made sure that there was absolutely no conflict of interest. A special thanks are due to the area chairs, area co-chairs and other people who put in extra work in both reviewing more papers in their respective areas at the subcommittee meeting. Those people include Roland Chin, Anil Jain, Shree Nayar, Bahram Parvin, George Stockman, John Tsotsos, P. Anandan, Kim Boyer, Larry Davis, Greg Hager, Martial Hebert, Dan Huttenlocher, Rangachar Kasturi, Yvan Leclerc, Jim Little, Rosalind Picard, Jean Ponce, Ishwar Sethi, Rick Szeliski, Richard Weiss and Larry Wolff.

We have strived to maximize fairness at every stage, from issuing the Call for Papers, to selection of the program committee, to selection of the reviewers for a paper, to the interpretation of a review. However, given the vagaries of the review process and the infeasibility of receiving authors' feedback, it is likely that there are papers whose contributions may have been overlooked. We extend our sincere apologies to the authors of such papers.

A conference of this size cannot be successful without the help and support of a great many people. We are especially grateful to the following people for their roles in organizing this conference: Khotaro Ohba, Hiroshi Kimura, and Marie Elm at Carnegie-Mellon University for their support in logging and keeping track of papers and reviews; Ginny Limtiaco at the University of California, Riverside for providing important secretarial support during the entire period from planning to organizing the conference; and Mary-Kate Rada, Penny Storms, Kerry Bedford, Anne Marie Kelly, and Maggie Johnson at the IEEE Computer Society for making various arrangements, enabling online registration, compiling the proceedings, helping in the preparation of budget, and performing the art work.

We would like to give you a warm welcome to CVPR 1996 and to San Francisco! We hope the creative new work presented in these pages provides the inspiration and challenges for exciting future research.

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# BAYESIAN IMAGE RESTORATION AND SEGMENTATION BY CONSTRAINED OPTIMIZATION

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## Abstract

*A constrained optimization method, called the Lagrange-Hopfield (LH) method, is presented for solving Markov random field (MRF) based Bayesian image estimation problems for restoration and segmentation. The method combines the augmented Lagrangian multiplier technique with the Hopfield network to solve a constrained optimization problem into which the original Bayesian estimation problem is reformulated. The LH method effectively overcomes instabilities that are inherent in the penalty method (e.g. Hopfield network) or the Lagrange multiplier method in constrained optimization. An additional advantage of the LH method is its suitability for neural-like analog implementation. Experimental results are presented which show that LH yields good quality solutions at reasonable computational costs.*

## 1. INTRODUCTION

Image restoration is to recover a degraded image and segmentation is to partition an image into regions of similar image properties. Both can be posed generally as image estimation when the underlying image or segmentation map is to be recovered from a degraded image. Due to various uncertainties, it is often posed as an optimization problem. A criterion often used in optimal image estimation is maximum *a posteriori* (MAP) probability. In MAP estimation, it is assumed that both the prior probability distribution of the true image class and the conditional probability distribution of the data are known. In many MAP formulations, a Markov random field (MRF) or equivalently a Gibbs distribution is used as the prior distribution which encodes contextual constraints of the image [12, 21, 4, 9]. The posterior probability is generally also a Gibbs distribution. Minimizing the posterior probability is equivalent to finding the configuration which minimizes the energy function in the Gibbs distribution. This is the MAP-MRF framework [12, 5, 18].

When pixel values are from a discrete set, such as in multi-level image restoration and segmentation, the minimization is combinatorial. Many methods have been proposed to-date for finding the energy minimum in a discrete space. The most well-known ones include the iterative conditional modes (ICM) [4] and simulated annealing (SA) [17, 12]. Other algorithms of similar nature include the highest confidence first (HCF) [6, 7].

In this paper, we present a novel method, called the Lagrange-Hopfield (LH) method, for MAP-MRF multi-level image restoration and segmentation in which an image can be textured. The original MAP problem is converted into a constrained optimization problem. The LH method then solves the constrained optimization. It combines the augmented Lagrangian multiplier technique [24, 14, 23] with the Hopfield network [15, 16]. This effectively overcomes instabilities inherent in the penalty method (*e.g.* Hopfield network) or the Lagrange multiplier method in constrained optimization. The resulting algorithm solves a system of unconstrained differential equations, and is suitable for neural-like analog implementation. Experiments in both image restoration and segmentation are shown to compare the LH method with the iterative conditional modes (ICM), highest confidence first (HCF) and simulated annealing (SA) algorithms. The results show that LH performs better than ICM, HCF and sometimes SA in terms of the minimized energy values and error rates. Yet it is much more efficient than SA; it quickly yields a good solution after dozens of iterations.

Although in this paper the LH is used for image restoration and segmentation only, the method is general enough also for solving other problems that can be formulated as combinatorial optimization. Successful applications have been obtained for graph matching [19] and traveling salesman problem [20].



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The rest of the paper is organized as follows: Section 2 introduces the basic MAP formulation with discrete valued MRF. Section 3 reformulates the MAP estimation, which is an un-constrained combinatorial optimization problem, as a constrained real optimization, and then describes the LH method for solving the latter optimization. Section 4 presents experimental comparisons. Conclusions are given in Section 5.

## 2. MAP-MRF FORMULATION

The underlying image signal is denoted as $f = \{f_i \mid i \in \mathcal{S}\}$ where $\mathcal{S} = \{1, \ldots, m\}$ is the set of sites where each $i \in \mathcal{S}$ indexes a pixel in the image lattice. Each pixel takes on a discrete value $f_i$ in the label set $\mathcal{L} = \{1, \ldots, M\}$ and the $f$ is the restored multi-level image or the segmented map. The spatial relationship of the sites, each of which is indexed by a single number in $\mathcal{S}$, is determined by a neighborhood system $\mathcal{N} = \{\mathcal{N}_i \mid i \in \mathcal{S}\}$ where $\mathcal{N}_i$ is the set of sites neighboring $i$. A single site or a set of neighboring sites form a clique denoted by $c$. In this paper, only up to pair-site cliques are considered.

The type of the underlying image $f$ can be blob-like regions or a texture pattern. Different types are due to different ways that pixels influence each other, *i.e.* different contextual interactions. Such contextual interaction can be modeled as MRFs. According to the Markov-Gibbs equivalence [3, 12], an MRF is a Gibbs distribution

$$P(f) = Z^{-1} \times e^{-\frac{1}{T}\sum_{c \in C} V_c(f)} \tag{1}$$

where $V_c(f)$ is the clique potential function, $C$ is the set of all cliques, $T$ is a temperature constant, and $Z$ is a normalizing constant.

Among various MRFs, the multi-level logistic (MLL) model [10, 8, 9] is a simple and yet powerful mechanism for encoding a large class of spatial patterns. In MLL, the pair-site clique potentials take the form

$$V_2(f_i, f_{i'}) = \begin{cases} \beta_c & \text{if } f_i = f_{i'} \\ -\beta_c & \text{otherwise} \end{cases} \tag{2}$$

where $\beta_c$ is the parameter for cliques of type $c = \{i, i'\}$, while the single site potentials is defined by

$$V_1(f_i) = \alpha_I \quad \text{if } f_i = I \in \mathcal{L}_d \tag{3}$$

where $\alpha_I$ is the potential for label value $I$. For the 8-neighborhood system, we use $\beta_1, \beta_2, \beta_3$ and $\beta_4$ for pairwise cliques in the 0°, 90°, 45° and 135° directions, respectively.

When the true pixel values are contaminated by identical independently distributed (i.i.d.) Gaussian noise, the observed data is

$$d_i = f_i + e_i \tag{4}$$

where $e_i \sim N(0, \sigma^2)$ is the zero mean Gaussian distribution with standard deviation $\sigma$. The conditional distribution of $d$ is

$$p(d \mid f) = \frac{1}{\prod_i^m \sqrt{2\pi\sigma^2}} e^{-U(d \mid f)} \tag{5}$$

where

$$U(d \mid f) = \sum_{i \in \mathcal{S}} \frac{(f_i - d_i)^2}{2\sigma^2} \tag{6}$$

The energy in the posterior distribution, $P(f \mid d) \propto e^{-E(f)}$, is

$$E(f) = \sum_{i \in \mathcal{S}} \frac{(f_i - d_i)^2}{2\sigma^2} + \sum_{\{i\} \in C} V_1(f_i) + \sum_{\{i,i'\} \in C} V_2(f_i, f_{i'}) \tag{7}$$

in which the MRF and noise parameters $\alpha$, $\beta$ and $\sigma$ are assumed known for the MAP-MRF estimation. The MAP estimate for restoration and segmentation is defined as

$$f^* = \arg\min_{f \in \mathcal{L}^m} E(f) \tag{8}$$

The interested reader is referred to [18] for a thorough representation on the MAP-MRF framework.

## 3. THE LH METHOD

The minimization of the energy function $E(f)$ is in the discrete space $\mathcal{L}^m$ and hence combinatorial. Existing methods for the above minimization problem include SA, ICM and HCF. Here we present the LH method.

### 3.1. MAP-MRF Estimation as Constrained Optimization

We convert the original combinatorial problem formulation, in which the optimization is performed in a discrete space $\mathcal{L}^m$, into a constrained optimization in a real space. A convenient way is to consider it as a continuous label assignment problem [25]. We use an $M$ element vector $p_i = [p_i(I) \mid I \in \mathcal{L}]$ to represent the state of the assignment for $i \in \mathcal{S}$. The real value $p_i(I) \in [0, 1]$ reflects the strength with which $i$ is assigned label $I$. The matrix $p = [p_i(I) \mid i \in \mathcal{S}, I \in \mathcal{L}]$ is the state of the assignment.

The energy with the $p$ variables is defined by

$$\begin{aligned} E(p) \;=\; & \sum_{i \in \mathcal{S}} \sum_{I \in \mathcal{L}} r_i(I)\, p_i(I) + \\ & \sum_{i \in \mathcal{S}} \sum_{I \in \mathcal{L}} \sum_{i' \in \mathcal{S}, i' \neq i} \sum_{I' \in \mathcal{L}} r_{i,i'}(I, I')\, p_i(I)\, p_{i'}(I') \end{aligned} \tag{9}$$