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Parallel Algorithms in Computer Vision

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Abstract

Nell'ambito di un Progetto dell'IEI-CNR, orientato alla soluzione di problemi della Computer Vision, sono state definite versioni parallele di algoritmi di ottimizzazione non convessa, e ne sono state studiate le prestazioni in termini di qualità delle soluzioni ottenute e dei tempi di calcolo. In particolare, sono state realizzate implementazioni parallele su Cray T3D del CINECA, per gli algoritmi Simulated Annealing, Mixed Annealing e Graduated Non-Convexity. Tali algoritmi sono stati applicati ai problemi del restauro di immagini e della stima del flusso ottico.

Computer Vision problems, and especially Early Vision problems, are characterized by an extremely high computational complexity. Nevertheless, they are suitable to be solved by means of highly parallel architectures. As typical examples of Early Vision tasks we recall image restoration, edge detection, optical flow estimation, stereo vision and image segmentation. Over the last few years, these problems have been studied at IEI-CNR in Pisa, with particular attention to image restoration and optical flow estimation, by means of edge-preserving techniques.

Most of Early Vision problems are ill posed, in the sense that they can have multiple solutions or be ill conditioned. Thus they are generally solved by reformulating them as the minimization of cost functions that incorporate a priori information in the form of stabilizers. As well known, the use of Bayesian estimation and Markov Random Field models (MRF) allows the local smoothness properties of real scenes and the geometry of their discontinuities to be effectively described. Nevertheless, the non convexity of the cost functions involved requires the use of extremely computational demanding stochastic relaxation algorithms, such as simulated annealing. Alternatively, deterministic sub-optimal algorithms, which produce satisfactory results, have been proposed. The most popular of such algorithms is the Graduated Non-Convexity (GNC) algorithm.

For the restoration of images, a GNC algorithm has been proposed based on a stabilizer which can gradually recover intensity discontinuities of different amplitudes [1]. The method has been successfully experimented for the noise suppression on biological images acquired by a fluorescence microscope, at low light intensity levels [2].

Stabilizers which implicitly address self-interacting discontinuities have also been analyzed. They are based on the use of sigmoidal functions of the intensity gradients [3]. This approach allows interactions of high order among the discontinuities to be taken into account, and analogue computational models to be used for minimizing the resulting cost function.

With the aim at reducing the computational costs of simulated annealing, a mixed annealing algorithm has been studied, based on MRF models with explicit discontinuities. In this algorithm, only the binary variables related to the discontinuity field (line process) are stochastically updated, while the continuous variables related to the intensity process are updated in a deterministic way.

Due to the strong non convexity of the problem, the use of GNC type algorithms to estimate the optical flow have been proved to be ineffective. Thus the problem has been faced by means of simulated annealing, assuming quantized values for the displacements. In [4] a new deterministic approach has been proposed, which reduces the optical flow estimation problem to a shortest path problem in a directed graph.

The visual reconstruction problems are characterized, other than by the computational complexity of non convex optimization, also by the high number of variables and data, so that exploiting massively parallel algorithms would be extremely useful.

Fortunately, the cost functions employed are expressed as the sum of local functions, so that their minimization is an intrinsically parallel problem. For the implementation of visual reconstruction algorithms, Multiple Instructions Multiple Data (MIMD) parallel machines are particularly suitable. In these machines, each processor has the task to process a given area of the image, and communications occur only between processors assigned to adjacent regions. Increasing the number of processing units, the size of the image area assigned to each processor decreases. Since communications between processors regard the pixels of the area border, the

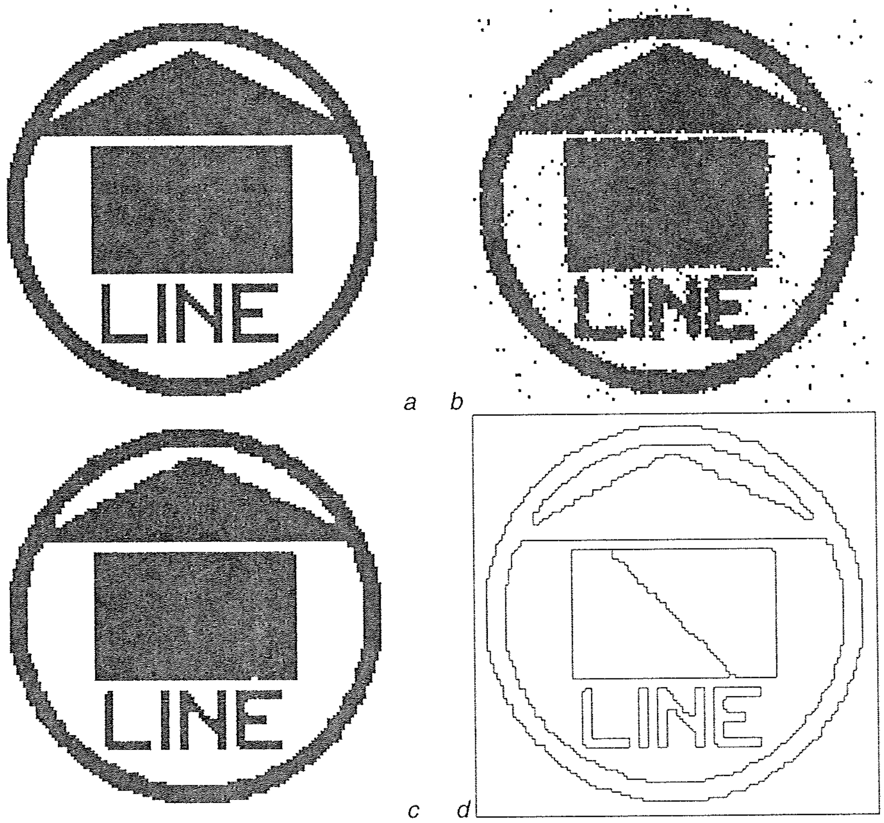

Figure 1 *Restoration of a 128×128 synthetic image: (a) original image; (b) image degraded by uniform blur and Gaussian noise; (c) image restored by mixed annealing; (d) edge map.*

number of the data to be exchanged decreases as the number of the processors increases.

In particular, both simulated annealing and mixed annealing are based on independent and asynchronous updates of the various elements of the field, so that these updates can be performed by processing units working in a substantially independent way. This further improves the efficiency of parallel architectures.

The algorithms for image restoration and optical flow estimation studied at the IEI have been implemented on Cray T3D, available at CINECA, and the performances of their parallel implementations have been analyzed [5].

It is straightforward to show that, when M processors are used, the speed-up for processing a $N \times N$ image is given by:

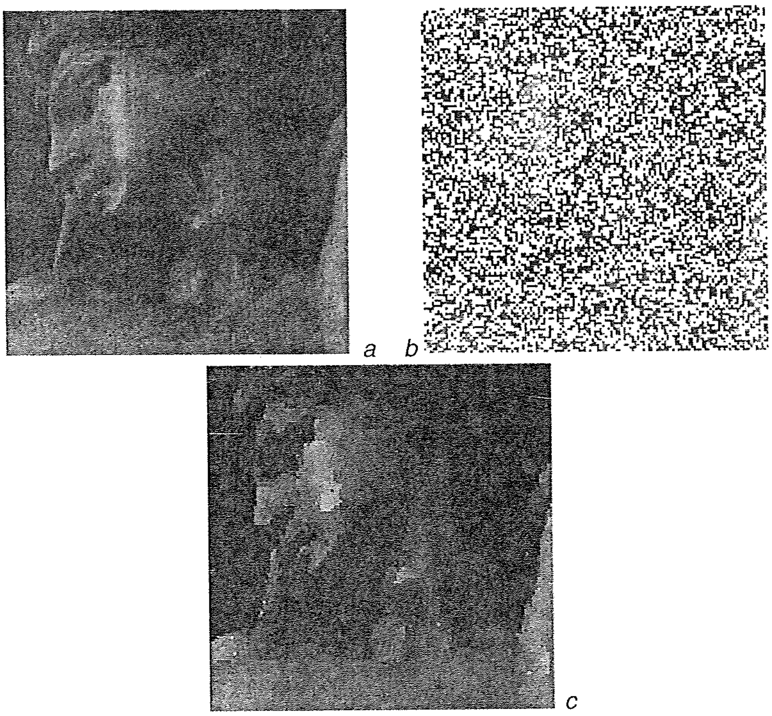

Figure 2 Restoration of a 128×128 real image: (a) original image; (b) image degraded by randomly suppressing 50% of the pixels and adding Gaussian noise; (c) image restored by GNC.

$$\frac{CN^2M}{kN\sqrt{M}+CN^2}$$

where C is the time for processing each pixel of the image and k is a constant related to the communication time between processors. In particular, for $M = 32$ and $N = 128$, we found a speed-up value of about 30.5.

As an example of our experiments, in Figure 1 the result of the restoration of a 128×128 synthetic image is shown. The degraded image was obtained by means of convolution with a uniform 3×3 mask and adding Gaussian noise with standard deviation $\sigma = 10$. The restored image, together with the corresponding edge map, was obtained using mixed annealing, and a MRF model with explicit discontinuities.

In Figure 2 the result of the restoration of a 128×128 real image is shown. The degraded image was obtained randomly suppressing 50% of the data and adding Gaussian noise with standard deviation $\sigma = 12$. The restored image was obtained using GNC, and a MRF model with graduated discontinuities.

Publications

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[5] **X. Qiao**
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