Demonstration of Video-Rate Optoelectronic Parallel Processors for Noise Cleaning in Binary Images by Simulated Annealing.

A. Cassinelli (1), Ph. Lalanne (1), P. Chavel (1) and I. Glaser (2)

(1) Institut d'Optique Théorique et Apliquée, CNRS, BP 147, 91403 Orsay Cedex, FRANCE

(2) 24 Hashnayim st., Givatayim 53230, Israel. This work was done while at the Department of Physics of Complex Systems, The Weizmann Institute of Science, Rehovot 76100, Israel.

Abstract

We present an optoelectronic stochastic artificial retina for binary image restoration, combining a Spatial Light Modulator, a CMOS circuit and an optical random number generator.

I) Optoelectronic processors for parallel simulated annealing.

I.1) Principles.

Many early and middle vision tasks such as restoration, image segmentation or even motion detection can be formulated as optimization problems consisting in finding the ground states of an energy function [1], [2]. This approach yields excellent results but, if implemented on conventional sequential workstations, the computational loads are too extensive for practical purposes. We have been studying implementations based on dedicated massively parallel integrated circuits, called stochastic artificial retinas [3], which minimize that energy at video-rate by simulated annealing. Our circuits are CMOS silicon chips built out of a mesh of processing elements (PEs), each having its own photodetectors and some computation abilities. We present here our latest experimental illustration, namely the demonstration of video rate simulated annealing for noise cleaning on a sequence of binary images. The input is provided by a binary ferroelectric liquid crystal SLM.

I.2) Illustration : noise cleaning on binary images.

Consider an input binary image X that results from degradation of an unknown binary original image X_o by binary « salt and pepper » noise that flips some of the « minus one » pixels to « ones » and conversely. The noise cleaning algorithm investigated assumes that the unknown original X_o consists of large patches of « minus ones » and « ones » and therefore enforces a continuity of the estimate (i.e. a priori knowledge about the image is that it has Markov Random Field [4] properties). The energy function selected for minimization is :

$$E(Y) = \sum_i \left(Y_i - X_i\right)^2 - \lambda^2 \sum_{i,j \in Neighborhood(i)} Y_i Y_j$$

The first term is an input fidelity term that tends to force pixel Y_i to its corresponding input pixel X_i. The second term in this equation is a convolution that tends to smooth the image (clique potentials in the MRF model). In our implementation, the neighborhood of each PE is limited to its four nearest neighbors. Minimization of the energy is therefore a compromise between input fidelity and noise smoothing (parameter λ allows us to weight the two terms).

If the unknown original image X_o is known a priori to be binary valued and the output Y is forced to be binary valued, then the problem is not trivial and no solution accessible in polynomial time is known : this amounts essentially to saying that the

minimum energy can only be found by exhaustive search in the space state, explaining the need for heuristic sub-optimal algorithms like simulated annealing [5]. Parallel Simulated Annealing can be used to compute a sub-optimal minimum. It preserves local computation and therefore it is suitable for Very-Large-Scale-Integration implementation. Indeed, the entire optoelectronic parallel processor only requires two functions : a) the computation of each local force ΔE_i (i.e. the energy variation when flipping Y_i from 1 to -1), including the input of the image X to be processed, and b) the update of the resulting estimate Y_i following the Heat-Bath sigmoid probability law :

$$\Pr\left(Y_i = 1\right) = \frac{1}{1 + \exp\dfrac{\Delta E_i}{T}}.$$

The system we implemented combines optics and electronic digital and analog circuitry. It is composed of three main devices. An 6x6mm^2 VLSI chip composed by 24x24 smart pixel array fabricated on 1µm CMOS technology [6] is in charge of the digital parallel computation of the local energy gradient (each PE being connected to its four nearest neighbors), while a speckle random-number generator [7] provides the circuit with 10000 spatially and temporally independent illuminations every microsecond (analog computation by differential detection of speckles has shown to be an efficient way to implement zero-mean Gaussian random sources ; the Heat-Bath sigmoid probability process of updating Y is thus obtained by simply comparing the random current with the local force [8]).Finally, the image to be processed is directly projected onto the chip from a Spatial Light Modulator device through simple imaging optics.

Following a statistical mechanics analogy, the chip alone implements evolution of a 2D Ising model at null temperature, while the speckle illuminations act as thermal noise sources. The input image acts like an external non-uniform magnetic field on the spin population. Annealing is simply obtained by decreasing the speckle laser power.

II) Principles of the experiment

II.1) Experiment goals

The aim of the present experiment is to study the performances of a video-rate optoelectronic simulated annealing image processor prototype over several sequences of binary images. To that purpose, we are now testing a system in which images can be presented to the retina in real time (up to 1250 images per second, although in this communication only 25 processed images per second results are shown). For the future, we are planning further possible developments bearing in mind that the noise cleaning problem is of fundamental though only academic interest.

II.2) Overview of the system architecture and operation

In its present state, our processor array operates as follows : a random initial state Y is generated on the control PC and sequentially sent to the processor chip. Control parameters setting the initial and final temperature and the number of test calculations are selected by the user. The constraint-to-the-data term of the energy expression is simply implemented by projecting the input image directly onto the PE's photodetectors. Our demonstrator uses a binary ferroelectric liquid crystal controlled by the computer, which forms and projects images in real time using a two lens coherent imaging system. The input image level can be adjusted for proper operation by either controlling the laser power of the SLM source or/and the driving current of the VLSI electronic interconnections.

The simulated annealing process is then started : the control PC drives the current of a second diode laser that illuminates a multimode fiber through a rotating diffuser, thus generating at the fiber exit face a temporally variable speckle pattern which is projected onto the detectors on the chip. The chip then runs the inner loop of the simulated annealing algorithm in parallel, achieving thermal equilibrium at the current temperature. The process iterates with the laser power being decreased as required to implement the temperature variation for annealing.

The main features of the system are shown in Figure 1. X is the input image to be processed and Y is the optimized result. T is the annealing temperature (i.e. the driving current of the laser diode), and λ weighs the PE interconnections (i.e. the driving current of the VLSI circuit with respect to the power of the SLM optical source).

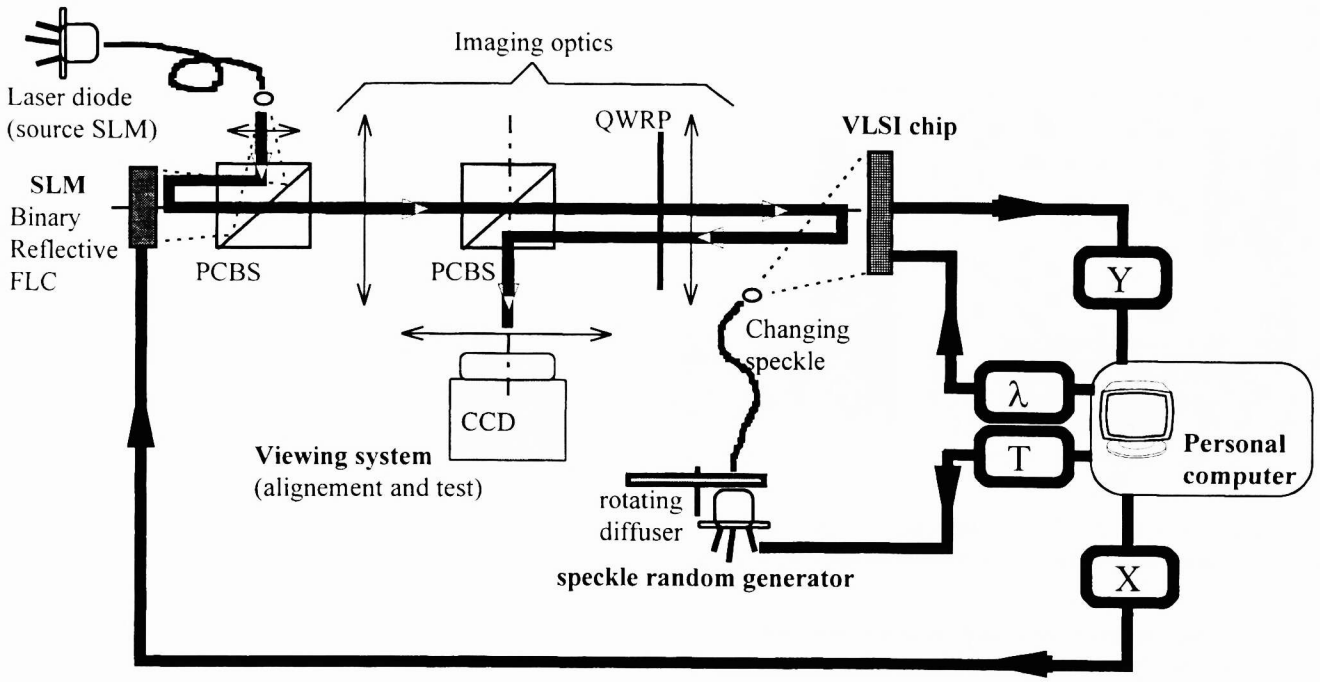

Fig.1: Optical architecture overview : PCBS stands for polarizing cube beamsplitters, QWRP for quarter wave retardation plate. White arrows represent the light beam path. Black arrows those of electric signals.

III) Experimental Results

III.1) Performance in terms of computing power

The processing time is 40 ms for one complete simulated annealing on the chip (25 Hz) ; typical values are 50 iterations of pixel updating at every temperature (to reach good thermal equilibrium), and 40 values for the temperature. One iteration takes about 20 μs (40ms/50/40) and is presently limited by the photodetector response time. The necessary optical power for the speckle and image input is on the order of a few milliwatts on the chip. This high value is related to the short integration time. As seen by the user, the annealing time is negligible in comparison with the time required for the dialogue between the control PC and the dedicated circuit.

III.2) Processor quality evaluation

Many tests were performed with the prototype to study the influence of analog computation inaccuracies on the overall system performance. Two of them are reported here. The first experimental test evaluates the ability of the prototype to sample under thermal equilibrium, when no image is presented to the chip (further results with projected images will be presented at the conference). The system is slowly annealed from a high temperature down to T1 and then again down to T2<T1. For each temperature, statistics of the energy landscape were collected under time evolution of the system. Theoretically, if samples are large enough the energy distribution would fit the canonical distribution at temperature T :

$$P(E,T)dE = C_T.\Omega(E).\exp\left[-\frac{E}{T}\right],$$

so that the logarithm of the ratio between distribution P(E,T1) and P(E,T2) will linearly depend on the energy, with a slope equal to : $m = \frac{T1 - T2}{T1.T2}$.

As expected, slight deviations from theoretical values are observed. They reveal digital-analog inaccuracies as well as sensitiveness of the algorithm performances to annealing parameters -like the decreasing rate of temperature- making precisely such a test a good procedure for supervising parameters.

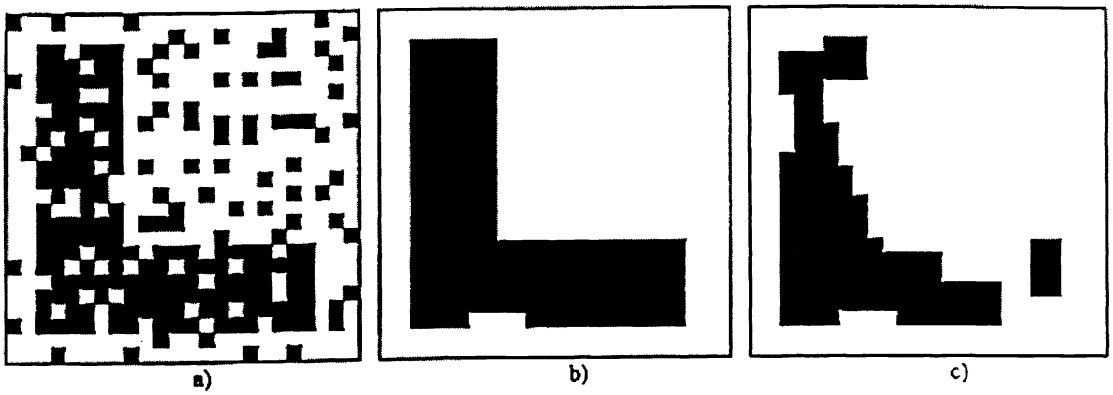

Fig. 2 : Experimental results. a) synthetic corrupted image. b) Restoration with speckle (annealing). c) Restoration without speckle (image trapped in a local minima of the energy).

The second test concerns the binary-image restoration problem. We have compared the restored image found by the prototype to the corresponding result from numerical computation. The test reported here has been accomplished using an engraved binary mask of a letter « L » degraded with 25% white channel noise (see Figure 2). The quality of the results compare well with all electronic, non-parallel simulations of the same process that require several minutes on a typical state-of-the-art PC : despite the analog inaccuracies, the system provides deep minima of the energy. Further comparisons are being carrying on for a whole set of images, thus allowing us to determine the average performances in more general situations (dependence on the image shape and angles). Experiments of this kind will lead to a good knowledge of the relationship between theoretical and experimental parameters ; eventually the prototype would be useful to quickly optimize the simulated annealing parameters for cleaning binary images. These results will be presented at the conference.

IV) Conclusion

With this fairly simple noise cleaning implementation we are pursuing the objective to demonstrate the interest of dedicated processing tasks for video real time parallel simulated annealing. In the future, we plan to extend the work in two directions : more complex image processing tasks and compact integration of the processor. Support of the European Commission under grant CI*CT93003 is gratefully acknowledge.

1 -S. Geman and D. Geman, « Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images », IEEE Trans Pattern Anal. Mach. Intel. PAMI6 721-741 (1984).
2 -P. Bouthemy and E. François, « Motion segmentation and Qualitative Dynamic Scene Analysis from an Image Sequence », International Journal of Computer Vision 10, pp 157-182 (1993).
3 -Ph. Lalanne, G. Prémont, D. Prévost, P. Chavel, « Stochastic Optoelectronic Retinae for Vision Tasks », Optical Computing `94, Edinburgh, August 1994, Proceedings, Institute of Physics Conference Series 139, 295-313 (1995).
4 -B. Chalmond, « Image restoration using an estimated markov model », Signal Process. 15, pp 115-129 (1988).
5 -S. Kirkpatrick, C.D. Gelatt and M.P. Vecchi, « Optimisation by simulated annealing », Science 220, 671-680 (1982).
6 -A. Dupret, « Etude de générateurs aléatoires pour machines cellulaires. Intégration d'une rétine stochastique opto-électronique », phD thesis, University of Paris Sud, december 1995.
7 -Ph. Lalanne, E. Belhaire, J.C. Rodier, A. Dupret, P. Garda and P. Chavel, « Gaussian random number generation by differential detection of speckles », Opt. Eng. 34, pp 1835-1837 (1995).
8 -G. Prémont, Ph. Lalanne, P. Chavel, M. Kuijk and P. Heremans, « Generation of sigmoid probability functions by clipped differential speckle detection », Opt. Comm. 129, pp 347-352 (1996).