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CELLULAR NEURAL NETWORKS: A GENETIC ALGORITHM FOR PARAMETERS OPTIMIZATION IN ARTIFICIAL VISION APPLICATIONS

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SOMMARIO

Si presenta un metodo per ottimizzare alcuni parametri di una rete neurale cellulare (CNN), basato sulle cosiddette Strategie Evolutive. Le matrici di connessione di retroazione così ottenute risultano essere più efficaci di quelle in letteratura, per il compito di estrarre alcune caratteristiche delle immagini che acquisisce un veicolo autonomo.

SUMMARY

An optimization method for some of the CNN's parameters, based on evolutionary strategies, is proposed. The new class of feedback template found is more effective in extracting features from the images that an autonomous vehicle acquires, than in the previous CNN's literature.

Cellular Neural Networks: a genetic algorithm for parameters optimization in artificial vision applications

Sergio Taraglio Andrea Zanela

1. Introduction

The Cellular Neural Networks (CNN) [1][2] represent a computational paradigm which have found many applications in the field of image processing.

In this work we investigate the possibility of using such an approach for the navigation of autonomous robotised vehicles. We present an application able to extract the information necessary for the guidance of an autonomous vehicle from some features of the environment such as the architectural lines. Through this visual information the vehicle will be able to determine its route inside an unknown, yet partially structured, environment[3][4].

In most of the CNN applications, the search for the right parameters for the network is based on trial and error search or on comparison with previously addressed problems. One possible method to find such parameters in a more objective way is represented by the genetic search in the solution space.

Here the optimization of some of the network parameters for the detection and isolation of the architectural lines in a corridor is performed through a genetic-like algorithm, the so called Evolution Strategies (ES's) [5][6].

The template automatically found by the algorithm is strikingly similar to the Laplace operator found in the literature [2], but it represents a generalization able to perform better, as requested, in real images especially if further processing is needed, e.g. extraction of vertical or horizontal lines, etc..

2. Feature Extraction

We approach our problem using synthetic 80x120 pixel images (with a depth of 8 bit) of an indoor environment such as the one in Fig. 1.a, this represents the image of a corridor as seen by the vision system of the autonomous vehicle. What we wish to obtain from our system is an output image as the one in Fig. 1.b, here all the principal architecture lines are well highlighted.

Figure 1: a) a synthetic image of an indoor environment, b) target image for architectural feature extraction.

One of the standard ways to obtain this result is through a Laplace operator, a differential operator able to detect grey level gradients in an image. A CNN implementation of such an operator uses as its feedback template (see e.g. [2]):

$$A = \begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix} \quad (1)$$

and for the other parameters of the circuit: $B = 0$; $C = 10^{-9} F$; $R_x = 10^3 \Omega$; $I = -1mA$.

The simulation begins with the "connection" of the input image to the CNN, using the grey level values as the initial states of the circuit $v_{xij}(0)$ of each cell. Then the circuits are made evolve all the way to their final stable state and the $v_{xij}(\infty)$ are downloaded and translated back into grey levels. Out of the characteristics of the CNN, the final values are in $\{-1, 1\}$, that can be represented as either black or white pixel values. Through the simulation of this CNN, we obtain as output the image in Fig. 2.

Figure 2: Output image using the Laplacian operator.

If we compare this output with our desired one (see Fig. 1.b), we observe two main issues:

- it has lost two principal architectural lines: the one separating the far away surface from the ceiling and the one from the left wall.

- it is extremely noisy.

At this point we may ask ourselves if it is possible to do better, finding a new set of CNN parameters able to obtain an image nearer to the desired one.

3. Evolution Strategies and their Application to CNN

The optimization algorithm we have chosen to pursue this aim is the so called Evolution Strategies (ES's). The ES's are stochastic optimization algorithms that utilize the genetic population metaphor to explore the domain of problem solutions.

The reason for this choice lays in the existence of two properties of this approach that we take as an advantage in our problem, which are not present in the standard genetic algorithms:

1. they work on real numbers strings and not on bit words, hence we don't need any coding
2. the strings are subject to a series of genetic operators, as in standard Genetic Algorithms[7], but here the main one is the mutation operator. The width of the mutation is determined multiplying the string by random deviates with a normal distribution with an expected value $\eta = 0$ and standard deviation σ .

An interesting feature of the ES's is that the standard deviation is itself subject to the genetic operator, in this sense it becomes one of the parameters that the algorithm optimizes, therefore the width of the mutation follows the search space of the problem's solutions.

In our approach we limit the parameters to be optimized to the nine components of the feedback template, keeping the others circuit elements of the cell constant.

Thus a typical member of the population which undergoes the algorithm is represented by the ten digit string:

1	2	3	...	8	9	10
A(1,1)	A(1,2)	A(1,3)	...	A(3,2)	A(3,3)	Standard deviation

Let us enter the details. We have two images, an input image to be processed, and a target image (IMT); the algorithm generates the starting population of k strings containing random numbers in $[-2,2]$ except for the A(2,2) element which is chosen in $[1,10]$ because of the stability constraint for CNN circuits (see [1]).

The fixed parameters of the cell are chosen as follows:

$$B = 0, C = 10^{-9} F, R_x = 10^3 \Omega, I = -1mA.$$

The associated CNN for all the k string in the population is then simulated, obtaining k evaluated images IM_k . Each image is compared with the IMT through the fitness function:

$$Fitness[CNN_k] = 1 - \frac{\sum_{i=1}^N \sum_{j=1}^M (pixel_{ij}[IM_k] - pixel_{ij}[IMT])^2}{4NM} \quad (2)$$

The 20% fraction of the population with the best fitness is cloned to restore the total number of string in the population with the due genetic operators. In Fig. 3 we present a scheme of the optimization's algorithm. The termination rule for the process is only the maximum number of iteration step, here 50000.

Figure 3: How the algorithm works.

After a number of trials we finally obtained the following template string:

-0.989 -1.002 -1.001 -1.001 12.013 -1.000 -1.000 -0.998 -0.997

The associated output image is as follows:

Figure 4: Output image.

In order to "clean up" the image we apply a cascade of CNN filters, namely one hole-filler [8] and one edge-detector (see Fig. 5.a and Fig. 5.b).

Figure 5: a) hole filler output, b) edge detector output.

The final image (Fig. 5.b) is strikingly similar to the desired one and much less noisy than what found through standard Laplacian operator (see Fig. 2).

The string found by ES's corresponds, unless one hundredth, to the feedback operator:

$$A = \begin{pmatrix} -1 & -1 & -1 \\ -1 & 12 & -1 \\ -1 & -1 & -1 \end{pmatrix} \quad (3)$$

which represent a generalization of the Laplace operator of the CNN's literature in (1). This new template, that we named Laplace-12, blindly found by the genetic approach, suggested to us the introduction of a new class of templates: the Laplace-n feedback operators, defined as follows:

$$Laplace - n = \begin{pmatrix} -1 & -1 & -1 \\ -1 & n & -1 \\ -1 & -1 & -1 \end{pmatrix} \quad (4)$$

4. Extracting Features from Real Images

When we consider the images that an autonomous vehicle may acquire in an indoor environment (see Fig.6), the advantages the new template is more evident.

Figure 6: An image of the indoor environment where the vehicle moves.

The size of these images is 100x160 pixel with a depth of 8 bit. Simulating the CNN which performs the standard laplacian operator as above said, we obtain the image in Fig. 7.a. If we are interested in finding in this image the vertical lines, applying the usual CNN filter we obtain the image in Fig. 7.b.

Figure 7: a) output image of the CNN computing the laplacian, b) vertical lines detected in Fig. 7.a.

It is evident that we have lost nearly all the information we seeked. Whereas simulating a CNN with the feedback operator above found with ES's, we get:

Figure 8: a) output of the CNN with $A=LAPLACE-12$, b) vertical lines detected in Fig. 8.a.

which represents a result more usable in the task of guiding a vehicle.

Let us now give the order of magnitude of the timings needed for such an output. Simulating the system on a DIGITAL ALPHA 4000-610 computer on a 100 x 160 real image, we spend about two seconds, while an estimate for an HW implementation of this CNN cascade is around $10\mu s$.

5. Conclusions

In this paper, the possibility of using CNN's for artificial vision in navigation problems was addressed. We have presented an application able to extract the information necessary for the guidance of an autonomous vehicle in non structured environments from some features of the environment such as the architectural lines.

Through the application of ES's we discovered a new class of CNN feedback templates, which performs better (and faster) in isolating the architectural lines of an indoor environment from TV input images than what previously used in these problems.

The solution of an hardwarised CNN for this kind of problems could be a viable solutions for a huge class of Artificial Vision problems. In fact once implemented in HW the CNN's can deliver an output in extremely short times, compatible with the real time requirements of robotised autonomous vehicles.

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