

Application of Direction Constrained and Bipolar Waves for Pattern Recognition

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ABSTRACT: *Direction constrained and bipolar waves are introduced. Their possible applications for direction selective curvature and concavity detection as well as region segmentation are shown. A CNN algorithm frame for feature-based object decomposition is presented. Algorithms are tested on the 64x64 CNUM chip.*

1 Introduction

Cellular Neural Networks (CNN)[1][2], the CNN paradigm [3] and the analogic computer, the CNN Universal Machine [4], provide a new computational approach to spatiotemporal computing in particular image processing. The recent implementation of the CNN Universal Machine (CNN-UM) architecture, an analog visual microprocessor [5], exhibits trillion operations per second in a single chip. Contrary to usual digital computing, the application of the CNN paradigm and analogic algorithms require a completely different way of thinking. Instead of sequentially repetitively executed arithmetic and logic instructions, the CNN analogic programs consist of the combination of logic and spatiotemporal analog operations. This analog operation - defined by a template - performs complex computational tasks in a single dynamic wave or process.

In this paper new propagating wave types are described in section 2 and some of their applications are presented in section 3. Algorithms are tested on the new 64x64 CNUM chip [5] in the CADETWin [6] and CCPS environment [7].

2 Special Propagating Waves

In section 2.1 a binary propagating wave is introduced, which propagates along a predefined direction and the propagation stops when a certain convex hull of the object is filled. The convexity is interpreted only into the direction of propagation. In section 2.2 a wave type is described that propagates symmetrically, but black and white waves spread simultaneously. When two differently colored waves bump they annihilate each other.

The input and the initial state of the network are the same in the case of both wave types.

2.1. Direction constrained wave

Trigger waves, which have symmetric generator template matrix, were discussed in detail in [8]. In this section a direction selective trigger-like wave is proposed. The propagation starts from those black pixels around which there is a properly oriented, L shaped pixel configuration (see Fig. 2) and propagates parallel; therefore, the wavefront has a straight edge shape. The angle of the direction of the normal vector of the propagating wavefront is denoted by α . Fig. 1 shows the interpretation of α .

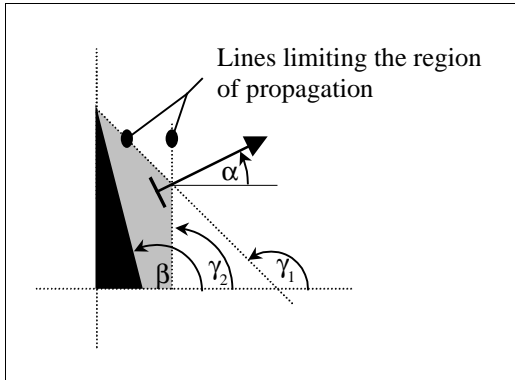


Figure 1: Direction constrained wave propagation. The Black area is the initial object. Symbol α is the angle of the normal vector of the propagation. β denotes the angle of the relevant boundary of the object. γ_1, γ_2 are the angles of the lines which bound the region that will be filled. The filled area is denoted by gray color.

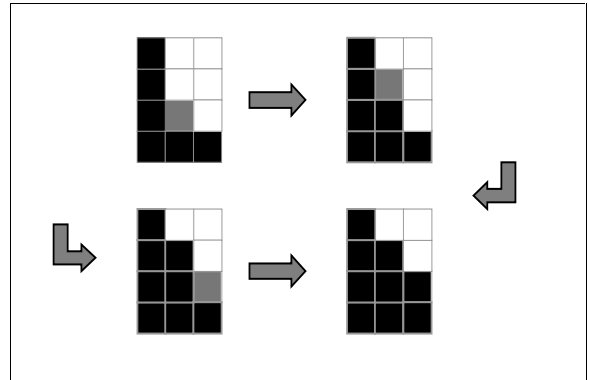


Figure 2: The result of the concavity filler template in a 3×4 sized window, $\alpha=26.56^\circ$. The stable pixels are denoted by black. Gray color denotes those pixels that are to be turned into black in the next step. Propagation occurs if there is a properly oriented, L shaped pixel configuration around a white pixel.

Propagation occurs if $\gamma_2 < \beta < \gamma_1$ and $\gamma_2 < \alpha + \pi/2 < \gamma_1$. This rule can be transformed into pixel level: those white pixels will be black which have black neighbours to north-west, south-west, south and white neighbour to north-east. Of course, this pixel configuration depends on the direction, which is expressed by α .

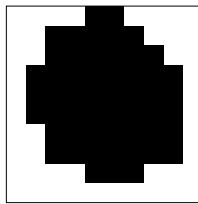
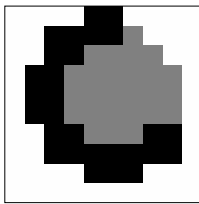


Figure 3: The result of the concavity filler template in a 10×10 sized window, $\alpha=26.56^\circ$. Gray color denotes those pixels that are to be turned into black.

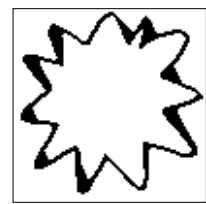
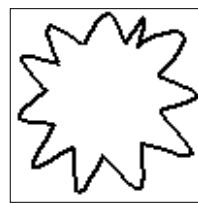


Figure 4: The Result of the concavity filler template., $\alpha=26.56^\circ$

Inequalities and templates for other directions can simply be produced by geometrical rotation and mirroring. In Fig. 2 and Fig. 3 the result of a concavity filler template can be seen when $\alpha=26.56^\circ$.

Possible α values and related A-template design

As a result eight different templates can be produced. Possible α values are:

$$\alpha = \arctan(\pm 0.5) + k2\pi, \alpha = \arctan(\pm 2) + k2\pi, k=0..1.$$

The following template generates propagation for the $\alpha=26.56^\circ$ ($\arctan -0.5$) direction:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \\ 1 & 1 & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad z = 2$$

This type of wave can fill regions where the tangents of object boundary points are within a prescribed range. This means that the concave segments of the object can be filled depending on the orientation of the concavity. The effect of the

template can well be observed in Fig. 4. The concavity template (which can be found in the CNN Software Library [10]) produces similar, but direction independent result.

2.2. Bipolar waves

All cells of a CNN-UM that compute a wave - except the cells changing in the wave front - are in one of the stable states: they are either black or white. However, there is a third, unstable state - the zero level -, which can be applied in computation. Thus, in the same structure two different wave types can be initiated: black waves starting from black patches and white waves triggered by white patches. Other empty areas are set to zero. When two, similarly colored waves collide, they join. But when two different waves collide, annihilation occurs. See Fig 5.

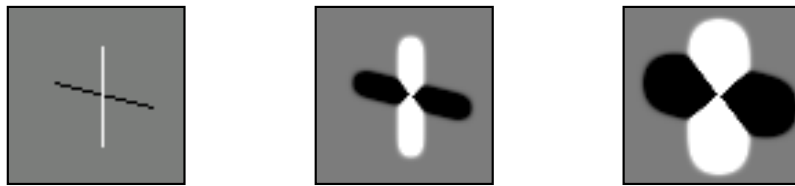


Figure 5: Transients of bipolar waves. When two different waves collide, annihilation occurs.

One possible template for this is:

$$\mathbf{A} = \begin{bmatrix} 0.3 & 0.3 & 0.3 \\ 0.3 & 0.8 & 0.3 \\ 0.3 & 0.3 & 0.3 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad z = 0$$

Since the speed of propagation of the black and the white waves are the same, the annihilation will occur half way between two different patches. The boundary where the annihilation occurs will be a line (Fig. 6).

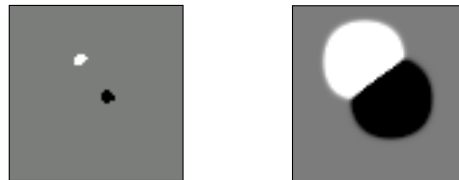


Figure 6: Waves of two patches. The annihilation zone divides the distance of the initial patches into two equal parts.

If more than two different patches are present, a continuous boundary consisting of line segments will be formed. Thus, if two point sets are given the region boundary can be approximated (Fig. 7).



Figure 7: Bipolar waves when three points are present. The annihilation zone consists of two line segments.

2.3. Curvature and concavity based object decomposition

One of the characteristic features which human recognition seems to be based on is the local curvature of objects. Several objects can well be described by the positions and relations of their curvature locations.

During his experiment, Fujita [8] found that in monkeys' inferotemporal cortex, there are neurone cells which are sensitive exclusively to specific complex shapes and patterns. This recognition is not a kind of template matching, but a much more robust process which can tolerate wide range changes of illumination and viewing angle of objects.

The CNN operation presented in section 2.1 is suitable for detection of differently oriented arc segments. Since the curvature is a scale invariant property, it can be an effective descriptor of objects.

Here a CNN algorithm frame for object classification is presented, where feature-based decomposition is applied first and then the resulting images are filtered by logic operations.

1. Apply the direction selective concavity filler template to the initial black and white images. Do this for all desired directions of arcs by applying the appropriately transformed template.
2. Subtract the original image from all of the result images and remove small patches and single pixels.
3. Form logic combinations of the result images of the previous step, which contain at this point only patches at the locations of selected concavities. By logic combination, direction selectivity can be improved.
4. Classify the patches by distance. As a result we get images on which patches are left that have specified distance and orientation compared to each other.
5. Make logic combination of the result images of the previous step.
6. Compose logic OR of each image. The result is a binary feature vector.

Steps 4 and 5 are not always necessary. The distance classification can be accomplished by applying the variants of shadow templates for projecting shadows of prescribed length into appropriate directions. If two images are given that contain patches, let the transient of shadow template run until it reaches the desired length in the first image. Then make logic AND of the two images. The result contains patches which fall into the selected direction and are not farther from the patches in the first image than the length of the projected shadow. The shadow template variants can be found in [10].

This algorithm skeleton is used for some applications which are presented in the following section.

3 Applications

In the following sections some applications of the formerly described methods and algorithm are presented. All the applied templates can be found in [10]. The algorithms were implemented in the new CADETWIn and CCPS environment.

3.1. Geon detection by analogic algorithm

By applying some of the previously described algorithm steps to two geons similar to the ones presented by Fujita [9] similar result can be reproduced on the 64x64 CNUM chip. An earlier CNN algorithm for this geon detection problem is presented in [11]. The flowchart of the algorithm can be seen in Fig 8. The basic idea is to select those objects in which an L and a horizontally mirrored L shape can be found close to each other. Closeness is evaluated by increasing the size of the patches and then composing the logic AND of the two images containing the patches. If two L shaped patterns are close enough to each other the intersection of them is not empty.

3.2. Hand orientation detection on the 64x64 CNUM chip

The algorithm's main steps are the same as in section 2.3 but the distance classification steps are left out. The input image is grabbed from a camera and then it is thresholded. After that concave regions falling into four directions are located by the template proposed in section 2.1. Then the direction selectivity is improved by logic combinations of the four images. Afterwards the original image is subtracted from the images and the small patches are removed. Finally binary decisions are made, based on whether the images contain black pixels or not. By more complex logic decision, more precise classification can be accomplished. Application of distance classification can further improve the accuracy of the detection.

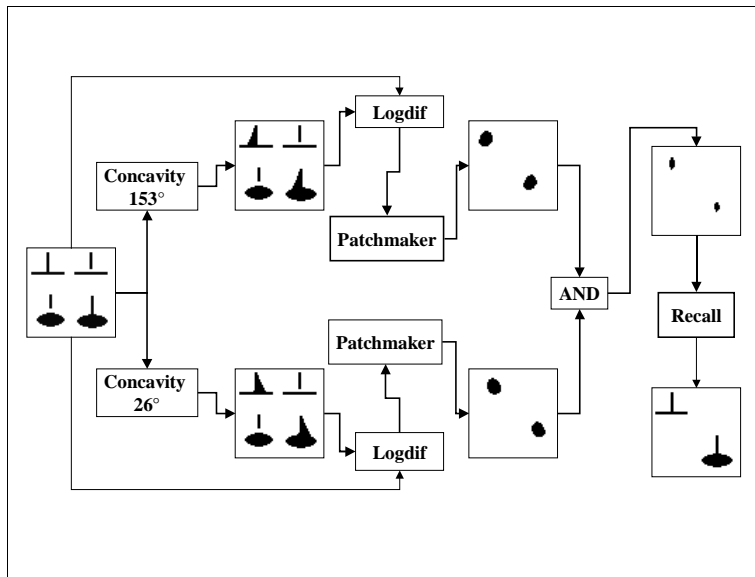


Figure 8: Selection of those objects which are similar to a flipped T. The text boxes contain the names of the applied templates and logic operations. All the operations are run on the 64x64 CNUM chip.

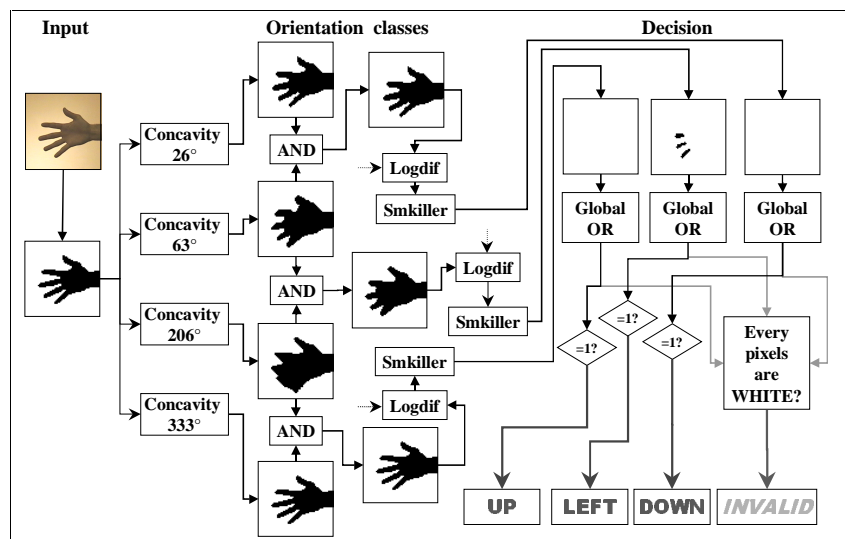


Figure 9: Hand orientation detection by the 64x64 CNUM chip. The dotted input line of **Logdif** symbolises the signal source from the black and white input images. The text boxes contain the names of the applied templates and logic operations.

3.3. Texton segmentation

The method is very similar to the one presented in section 3.1. At first the different textons are detected by the algorithm mentioned previously in section 2.3. Then a composite image is created from the two resulting images containing the two texton sets with different a color. The region boundary is detected by bipolar waves described in section 2.2.

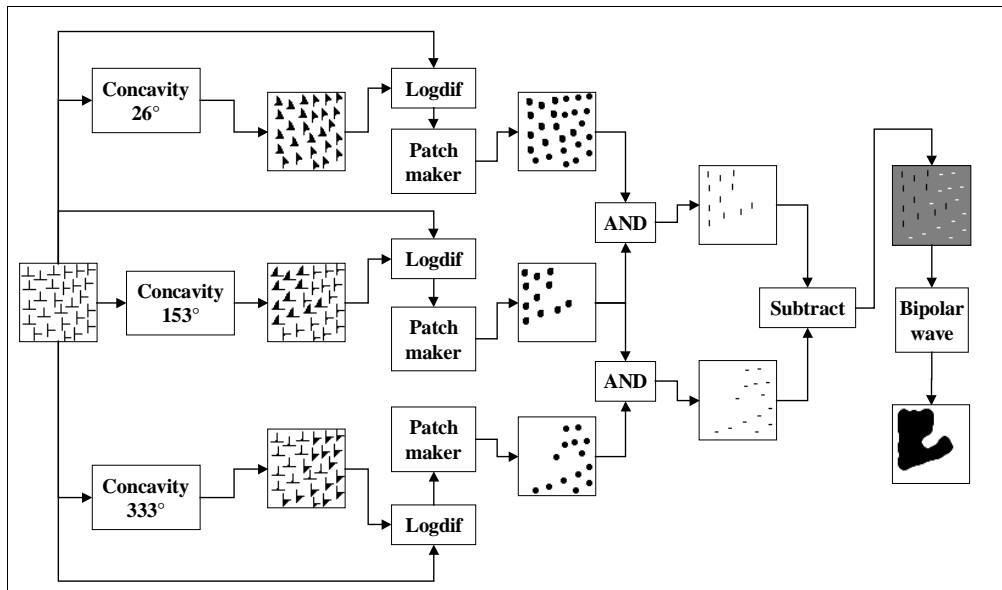


Figure 10: Texton segmentation. The text boxes contain the names of the applied templates and logic operations. The final image contains the regions.

4 References

- [1] L.O. Chua and L. Yang, "Cellular Neural Networks: Theory", IEEE Trans. on Circuits and Systems, (CAS), Vol.35. pp. 1257-1272, 1988.
- [2] L.O. Chua and L. Yang, "Cellular neural networks: Applications", IEEE Trans. on Circuits and Systems, (CAS), Vol.35. pp. 1273-1290, 1988.
- [3] L.O. Chua and T. Roska, "The CNN paradigm", IEEE Trans. on Circuits and Systems I: Fundamental Theory and Applications, (CAS-I), Vol.40, No. 3, pp. 147-156, 1993.
- [4] T.Roska and L.O.Chua, The CNN universal machine: an analogic array computer, IEEE Trans. on Circuits and Systems II: Analog and Digital Signal Processing Vol. 40, No. 3, pp. 163-173, 1993.
- [5] S. Espejo, R. Dominguez-Castro, G. Linan, A. Rodriguez-Vázquez, "A 64x64 CNN Universal Chip with Analog and Digital I/O", Proceedings of 5th IEEE International Conference on Electronics, Circuits and Systems, (ICECS'98), pp. 203-206, Lisboa, 1998.
- [6] P. Szolgay, K. László, L. Kék, T. Kozek, L. Nemes, I. Petrás, Cs. Rekeczky, I. Szatmári, Á. Zarándy, S. Töld and T. Roska, "The CADETWin Application Software Design System - A Tutorial", European Conference on Circuit Theory and Design - ECCTD'99, Design Automation Day proceedings, (ECCTD'99-DAD), Stresa, Italy, 1999, in print.
- [7] Á. Zarándy, T. Roska, P. Szolgay, S. Zöld, P. Földesy and I. Petrás, "CNN Chip Prototyping and Development Systems", European Conference on Circuit Theory and Design - ECCTD'99, Design Automation Day proceedings, (ECCTD'99-DAD), Stresa, Italy, 1999, in print
- [8] Cs. Rekeczky and L.O. Chua, "Computing with Front Propagation: Active Contour and Skeleton Models in Continuous-Time CNN", Journal of VLSI Signal Processing Special Issue: Spatiotemporal Signal Processing with Analogic CNN Visual Microprocessors, (JVSP Special Issue), Kluwer, 1999 November, in print.
- [9] I. Fujita, K. Tanaka, M. Ito and K. Cheng, "Columns for visual features of objects in monkey inferotemporal cortex", Nature 360, pp. 343-346, 1992.
- [10] CNN Software Library (Templates and Algorithms) Version 7.3, Edited by T. Roska, L. Kék, L. Nemes, Á. Zarándy, and P. Szolgay, DNS-CADET-15, Computer and Automation Institute, Hungarian Academy of Sciences, Budapest, 1999.
- [11] K: LOTZ, Á. ZARÁNDY, T. ROSKA, J. HÁMORI, An Analogic Phenomenological CNN Algorithm to Model the Mouth Detection Task of the Inferotemporal Cortex Discovered by I. Fujita, in Proc. NOLTA'95, International Symposium on Nonlinear Theory and Appl, Vol.2. pp. 717-722, Las Vegas, 1995.