IEEE Int. Workshop on Nonlinear Dynamics of Electronic Systems (NDES-98), pp. 137-140, Budapest, Hungary, July 16-18, 1998.

THE CNN IMPLEMENTATION OF WAVE TYPE METRIC FOR IMAGE ANALYSIS AND CLASSIFICATION

István Szatmári[1] and Tamás Roska[1, 2]

[1]*Analogical and Neural Computing Laboratory, Computer and Automation Institute,*
Hungarian Academy of Sciences, Kende u. 13-17, H-1111 Budapest, Hungary
[2]*Electronics Research Laboratory, College of Engineering,*
University of California at Berkeley, Berkeley, CA 94720, USA

E-mail: szatmari@lutra.sztaki.hu, roska@lutra.sztaki.hu

***Abstract* - In this paper a CNN based wave type metric is discussed and designed for object classification. The autowave metric, a nonlinear variant of the Hausdorff metric, is used. This approach turned out to be superior compared to some other classification methods, e.g. the Hamming distance calculation. A number of tests have been completed within the so-called bubble/debris segmentation experiments using original and artificial gray-scale images [13, 14]. Here, we show the details of the CNN implementation and discuss its properties. The single-layer trigger wave generation and the two-layer implementation of wave type metric results in a flexible and efficient tool for object classification. The VLSI complexity of the proposed solution is also analyzed.**

I. INTRODUCTION

Since the publication of the original paper in 1988 [1], the rapidly growing field of Cellular Neural Networks (CNNs) have found numerous potential applications, especially in image processing problems where real-time signal processing is required [2, 3]. Pattern recognition and object classification are central problems in image processing as well. Their major task is to determine the extent to which one shape differs from another. There are several methods that can all be viewed as techniques for image classification or recognition via comparison with prototypes (pattern matching). This comparison requires the measurement of the coincidence of two different overlapping point sets. One possibility is to compute the Hamming distance between objects. Another known distance metric is the Hausdorff metric which is more tolerant to shift and noise [4]. A variant of this latter (nonlinear) metric is called autowave metric and provides an increased tolerance to noise effects [0]. The goal is to develop a shape comparison method that is efficient to compute, and produce intuitively reasonable results. Here, it will be shown that the Hausdorff distance or its variant, the autowave metric is often superior to the Hamming distance computation. We focus primarily on autowave metric. This approach can easily be implemented on CNN resulting an efficient, fast, and robust tool for object classification. Its use was already reported in [13, 14].

Limits of Hamming Distance

The most obvious criterion of the degree of coincidence of points sets is a measure of symmetrical difference (number of different points). It is obvious that this so called Hamming distance is sensitive to object shift and noise. Another problem is that in several cases the Hamming distance gives opposite judgment than a human observer would. Fig. 1 shows a simple example. The Hamming distance cannot measure the shape similarity, only the differences. It will be shown that another distance metric, e.g. autowave metric is more proper for this type of

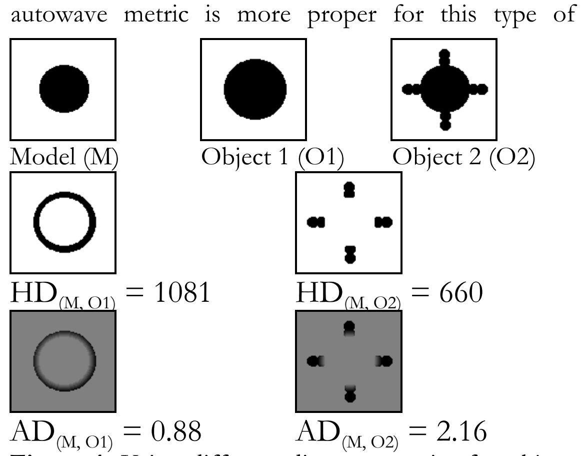


Figure 1: Using different distance metrics for object matching. Object O1 resembles more model M than object O2. Objects are positioned so the Hamming distances result in lowest values. The autowave metric chooses object O1 like a human observer would, while Hamming distance cannot take into account the shape information.

IEEE Int. Workshop on Nonlinear Dynamics of Electronic Systems (NDES-98), pp. 137-140, Budapest, Hungary, July 16-18, 1998.

classification where shape information is very important.

II. AUTOWAVE METRIC ON CNN

Autowaves

The autowave approach has several advantages for pattern recognition [0]. Autowaves represent a particular class of nonlinear waves which spread in active media at the expense of the energy stored in the medium [6, 7]. Autowaves can be described by a PDE of the form

$$\frac{\partial u}{\partial t} = D\left[\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right] + f(u) \tag{1}$$

Here, $\partial u/\partial t$ for an image, is the rate of change of intensity values u(x, y, t). It is induced by f(u) plus the diffusion term $D\cdot(\partial^2 u/\partial x^2 + \partial^2 u/\partial y^2)$. Eq. (1) describes an autowave if f(u) satisfies some requirements. It should be describe a time-varying or a nonlinear interaction. We will focus on the simplest type of autowaves called traveling or trigger waves where the transition from state -1 to state 1 of a cell can propagate in the array. It should be noted that trigger waves do not have the annihilation property. We only need the conservation of amplitude during propagation.

Implementation of trigger wave on CNN

Applications proposed for using autowave metric [0] can be realized by a CNN structure. Such a system can be built using Chua s circuits as cells [8, 9], or with the original cell-type but with a delay-type template [10, 11]. Here, the possible simplest solution was chosen for trigger wave generation, namely, waves propagate on a single-layer architecture with the original cell-type and the active local dynamics are generated with a simple nonlinear function. This takes into account the problem of the VLSI implementation. By proper discretization of Eq. (1) we obtain:

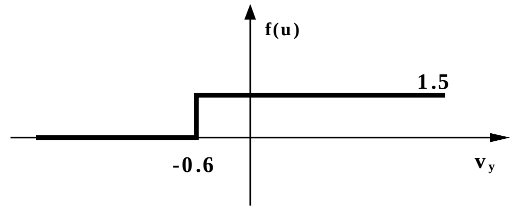
$$\frac{d}{dt}u(x,y,t) = D\left(\frac{\partial^2 u(x,y,t)}{\partial x^2} + \frac{\partial^2 u(x,y,t)}{\partial y^2}\right) + f(u)$$

$$\approx D\frac{1}{4}\left(u_{ij-1}(t) + u_{ij+1}(t) + u_{i-1j}(t) + u_{i+1j}(t)\right) - Du_{ij}(t) + f(u_{ij})$$

The autowave equation can be directly mapped onto the CNN array (*D*=1) resulting in the following simple template

$$A = \begin{bmatrix} 0 & 0.25 & 0 \\ 0.25 & 0 & 0.25 \\ 0 & 0.25 & 0 \end{bmatrix}, \quad \hat{A} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & f(u) & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad B = 0, \quad I = 0$$

In the middle of template *A* the effect of -1/R in the CNN equation is considered (R=1). The term f(u) is the following.



The initial state should contain the trigger points of the autowaves. Although the f(u) is the simplest nonlinearity useable for trigger waves it is still not available on the existing CNN chips. The advantages of this implementation is that the speed of the waves can be adjusted.

Implementation of wave type metric on CNN

Below we discuss in details how the autowave approach can be applied to the problem of image classification or recognition via comparison with prototypes (pattern matching). A variant of the Hausdorff metric called autowave metric which has several advantages over Hausdorff metric will be used in our experiments [0]. Fig. 2 shows the interpretation of the autowave distance. The properties of autowave distance provide increased tolerance to noise effects than Hausdorff distance. For instance, if two images exactly coincide, except for only one exceeding pixel apart from the image, then the Hausdorff distance may be large depending on the position of the exceeding pixel, whereas the autowave distance between these images would be zero.

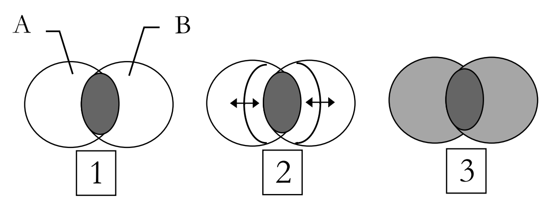


Figure 2: Autowave distance between point sets. (1) Two partially overlapping point sets. (2) The autowave spreads from the intersection through the union of point sets. (3) The wave propagates until all the points belonging to the union of point sets become triggered. The symmetric autowave distance is the time required to occupy the union and it can be used as a measure of the difference between A and B.

Fig. 3 shows a possible implementation of the autowave metric on CNN. The advantage of this two-layer implementation is that several object-model pairs can be compared at the same time.

IEEE Int. Workshop on Nonlinear Dynamics of Electronic Systems (NDES-98), pp. 137-140, Budapest, Hungary, July 16-18, 1998.

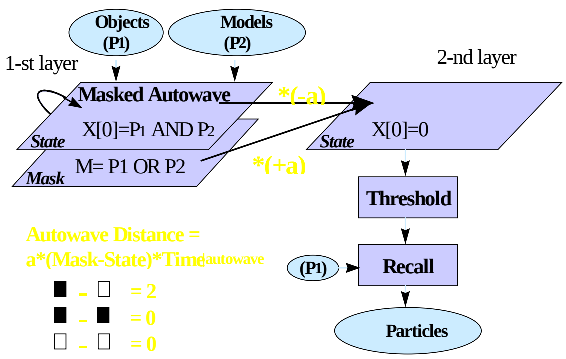


Figure 3: Implementation of wave metric on CNN. From the intersections of sets to be compared trigger waves propagate on the first layer and time is measured via constant current filling on the second layer. The current term has only three possible combinations.

The 2-nd layer is filled with a constant current to measure the time while waves are propagating on the 1-st layer. At the end of the process the cells at boundaries of the unions of objects and models will contain the highest voltage levels. This will be thresholded and indicate large difference if any. At last those objects will be recalled where these differences are large.

III. COMPARING HAMMING DISTANCE TO AUTOWAVE METRIC

Advantages of wave type metric

Here we try to explain why the autowave metric is more natural for object classification than Hamming distance. We consider the case where the classification is based on object and model (prototype) matching. The major problems of Hamming distance are the sensitivity to shift (position error) and noise. Another important bottleneck is that it does not take into account any shape information of objects. The advantages of autowave metric are the following. First, the computed distance mainly depends on shape similarity and not only on differences (Fig. 4). Second, the autowave metric is less sensitive to position error than Hamming one (Fig. 5).

IV. DISCUSSION

The Hamming distance is unambiguous at a given image resolution while autowave metric depends also on settings of autowave generation, i.e. the level of the diffusion term and properties of the active local dynamics (f(u)). This might cause some undesired effects. Fig. 6 shows the dependence of speed of wave propagation if the wave propagates on lines with

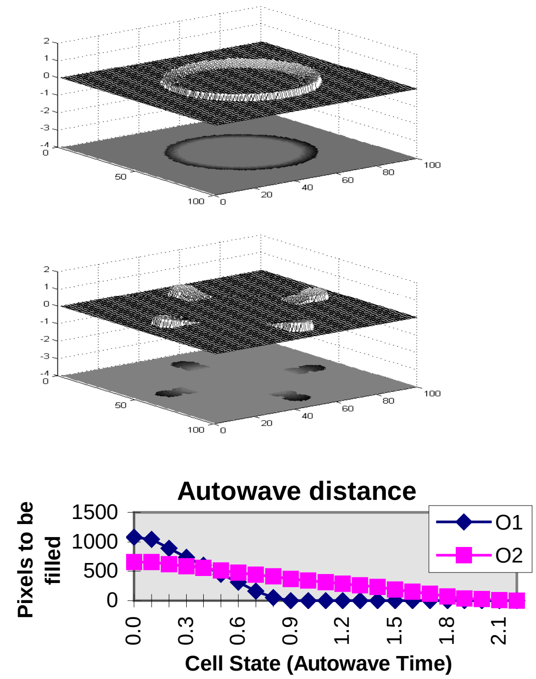


Figure 4: Autowave distances between model and objects presented in Fig. 1. The upper two images show layers filled with constant current. The voltage level of a cell corresponds to the time which is required for an autowave to reach a given cell. The diagram shows that autowaves fill in earlier the union of round shaped object and circle model than the object containing several extensions although the two circles differ more in sense of Hamming distance.

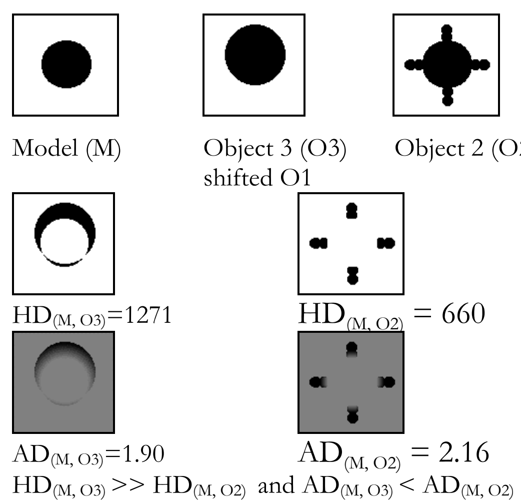


Figure 5: Illustration of sensitivity of distance metrics to position errors. The Hamming distance is very sensitive while autowave distance is much less.

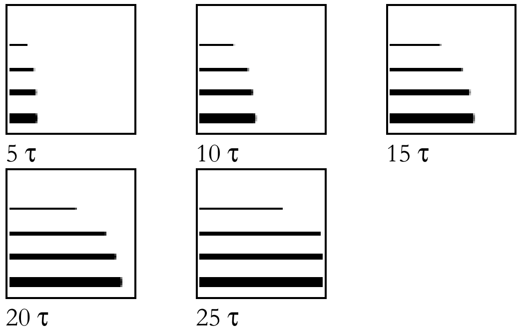


Figure 6: The speed of wave propagation strongly depends on settings of wave generation. In example, image size is 64x64 and lines widths are 1, 2, 3, and 5 pixels. The active local dynamics - f(u) has strong effect on speed of propagation. The ideal case is if the propagation on a one pixel wide line is equal with the speed on a more pixel wide line. Speeds of wave propagation are on a 1-pixel wide line: 1.7 pixel/τ. and on a more-pixel wide line: 3 pixel/τ

different widths. This dependence always occurs due to the diffusion term in Eq. 1. This effect can be eliminated if the f(u) triggers the state of a cell very fast, i.e. the breakpoint is near to the lowest value of cell s output and the value of the f(u) is high enough. By proper settings, the speed of wave propagation might be independent of object s wide, although it is very fast and this requires high accuracy in current. Considering the VLSI complexity, feasible solution can not avoid this dependence. This means that objects and models should not have sharp edges and thin lines but the one-pixel wide extensions are only critical parts.

V. CONCLUSIONS

We have described a possible implementation of wave type metric on CNN for object segmentation and classification. The discussed solution requires the so-called fixed-state map technique, and nonlinear cell interactions. The VLSI implementation complexity of the solution mainly depends on the implementation of wave generation, since this is the only building block which require nonlinear template interaction. Although the proposed CNN solution of wave type metric has undesired effects, it turned out to be more efficient for object classification than another methods.

REFERENCES

[1] L. O. Chua and L. Yang, *Cellular Neural Networks: Theory and Applications*, IEEE Trans. on Circuits and Systems, Vol. 35, pp. 1257-1290, Oct. 1988.

[2] L. O. Chua, and T. Roska, *The CNN Paradigm*, IEEE Trans. on Circuits and Systems, Vol. 40, pp. 147-156, March 1993.

[3] T. Roska and L. O. Chua, *The CNN Universal Machine*, IEEE Trans. on Circuits and Systems, Vol. 40, pp. 163-173, March 1993.

[4] D. P. Huttenlocher, G. A. Klanderman, W. Rucklidge, *Comparing Images Using the Hausdorff Distance*, IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 15, No 9, September, 1993.

[5] V. Biktashev, V. Krinsky, H. Haken, A wave *approach to pattern recognition (with application to optical character recognition)*, Int.l Journal of Bifurcation and Chaos, Vol. 4, No. 1, pp. 193-207, 1994.

[6] H. Haken, Synergetics, Springer, Berlin, 1978.

[7] V. Krinsky, ed., *Self-Organization. Autowaves and Structures Far from Equilibrium. Synergetics*, Vol. 28, Springer, Berlin, 1984

[8] L. O. Chua, M. Hasler, G. S. Moschytz, and J. Neirynck, *Autonomous Cellular Neural Networks: A Unified Paradigm for Pattern Formation and Active Wave Propagation*, IEEE Trans. Circuits Syst., Part I, Vol. 42, No. 10, pp. 559-577, 1995.

[9] V. Perez-Munzuri, V. Perez-Villar, and L. O. Chua, *Autowaves for image processing on a two-dimensional CNN array of excitable nonlinear circuits: flat and wrinkled labyrinths,* IEEE Trans. Circuits Syst., Vol. 40, pp. 174-181, Mar. 1993.

[10] T. Roska, L. O. Chua, D. Wolf, T. Kozek, R. Tetzlaff, and F. Puffer, *Simulating Nonlinear Waves and Partial Differential Equations via CNN-Part I: Basic Techniques*, IEEE Trans. Circuits Syst., Part I, Vol. 42, No. 10, pp. 807-815, 1995.

[11] T. Kozek, L. O. Chua, T. Roska, D. Wolf, R. Tetzlaff, F. Puffer and K. Lotz, *Simulating Nonlinear Waves and Partial Differential Equations via CNN-Part II: Typical Examples*, IEEE Trans. Circuits Syst., Part I, Vol. 42, No. 10, pp. 816-820, 1995.

[12] Á. Zarándy, A. Stoffels, T. Roska, F. Werblin, and L. O. Chua, *Implementation of Binary and Gray-Scale Mathematical Morphology on the CNN Universal Machine*, Memo No. UCB-ERL, Univ. of Cal. Berkeley, 96/19, 1996.

[13] István Szatmári, Abraham. Schultz, Csaba Rekeczky, Tamás. Roska, and Leon O. Chua, *Bubble-Debris Classification via Binary Morphology and Autowave Metric on CNN*, Berkeley Memo, University of California, Berkeley, M97/97, 1997

[14] Abraham. Schultz, Csaba Rekeczky, István Szatmári, Tamás. Roska, and Leon O. Chua, *Spatio-temporal CNN Algorithm for Object Segmentation and Object Recognition*, CNNA- 98, IEEE Int. Workshop on Cellular Neural Networks and their Applications, London, April 14-19, 1998.

IEEE Int. Workshop on Nonlinear Dynamics of Electronic Systems (NDES-98), pp. 137-140, Budapest, Hungary, July 16-18, 1998.

THE CNN IMPLEMENTATION OF WAVE TYPE METRIC FOR IMAGE ANALYSIS AND CLASSIFICATION

CORRESPONDENCE
István Szatmári

Analogical and Neural Computing Laboratory, Computer and Automation Institute,
Hungarian Academy of Sciences, Kende u. 13-17, H-1111 Budapest, Hungary

E-mail: szatmari@lutra.sztaki.hu
Phone: (+36)-1-209-53-57