Morphology and Autowave Metric on CNN
Applied to Bubble-Debris Classification

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Abstract

In this study, we present initial results of cellular neural network (CNN) based autowave metric to high
speed pattern recognition of gray scale images. The application is to a problem involving separation of metallic
wear debris particles from air bubbles. This problem arises in an optical-based system for determination of
mechanical wear. This research focuses on distinguishing debris particles suspended in the oil flow from air
bubbles and aims to employ CNN technology to create an on-line fault monitoring system. For the class of
engines of interest bubbles occur much more often than debris particles and the goal is to develop a
classification system with an extremely low false alarm rate for miss-classified bubbles. The designed analogic
CNN algorithm detects and classifies single bubbles and bubble groups using binary morphology and
autowave metric. The debris particles are separated based on autowave distances computed between bubble
models and the unknown objects. Initial experiments indicate that the proposed algorithm is robust and
noise tolerant and when implemented on a CNN Universal Chip it provides a solution in real time

Keywords - Cellular Neural Networks, Hamming and Hausdorff distances, autowave metric, model
based classification

1. Introduction

Cellular Neural Networks (CNNs) [1-3] are promising candidates for solving image
processing problems in which real-time signal processing is required. CNNs are cellular,
analog, programmable and multidimensional processing arrays with distributed logic
and memory. The processing elements are locally connected. The extension of the CNN

\[ ^1 \] analog and logic
paradigm is the CNN Universal Machine (CNNUM) in which distributed and global memories and logic functions support the execution of complex analogic algorithms. The key feature of the CNN architecture is its high operation speed.

In this paper we present initial results of analysis in which the main task is to distinguish air bubbles from debris particles. This problem arises in the optical detection of mechanical wear debris in highly aerated lubrication flows. The basic idea behind the analysis is the comparison of all particles to bubble models (circles and overlapping circles) and the classification based on a difference error measurement. The problem of distinguishing debris particles from air bubbles is difficult due to the coarse resolution of the images and to the requirement for an extremely low false alarm rate for miss-classified bubbles at a very high processing speed. It will be shown that CNN technology is a promising candidate to solve this problem which requires high-speed image processing and compact design.

The paper is organized as follows. Section 2 describes the bubble debris problem and analyzes a test system. Section 3 shows the advantages of a CNN based solution. Section 4 presents a possible algorithm based on binary morphology operations and autowave metric. Section 5 discusses the CNN implementation of the presented algorithm and autowave metric. Finally, Section 6 shows some examples from the experimental results and Section 7 draws the conclusions.

2. System Specifications and the Present Test System

At the NRL (Naval Research Laboratory) a bubble-debris classifier is being developed. Figure 1 shows the test environment in which the imaging system is applied. The imager device is located in the lubrication flow system which has a flow speed up to 10 m/s. A pulsed laser illuminator projects an image of the fluid along with various suspended objects onto a CCD sensor. These images are to be processed and analyzed by the system. The present test system processes binary images of 512x512 pixels on line, using a high speed serial processor. More details of the present system are provided in [4,5].

![Figure 1](image_url)

Figure 1 Optical sensing setup for the condition monitoring system

Figure 2 shows a typical image to be processed. This image contains debris particles and air bubbles some of which overlap due to occlusion. The major goal is to distinguish debris particles from the air bubbles.
The approach followed at NRL was to tune the system parameters to achieve the desired false alarm rate and to minimize the percentage of miss-classified debris particles. The system operates as a series of rejection filters with increasing time consuming classification tasks applied to a smaller and smaller number of objects. The strategy of using a sequence of tests for increasing computational complexity was determined by the limitations of the standard (digital) single CPU computer. This approach makes the classification algorithm difficult to tune in that the thresholds used for one test can impact on subsequent tests.

The CNN offers the possibility of a totally different approach to the bubble-debris classification problem. The features defined in the NRL system cannot be easily implemented in this environment and it is necessary to define a new feature set.

3. CNN-based Solution

Figure 3 shows the setup of the proposed architecture. A significant advantage offered by the CNN is that the image processing takes place close to the optical sensor alleviating the need for high throughput data transfer and only low-bandwidth, high relevance data is transferred from the sensor that is easily tackled by conventional digital hardware. This results in significant speedup in processing and decreases the size of the apparatus that mounts directly on the gearbox.
The CNN processor can be used to solve the following tasks:

A) size classification (to filter too small objects)
B) air bubble / non-bubble detection (to filter extraneous objects)

Figure 4 shows the block diagram of the proposed approach.

There are well-studied methods for size classification in the CNN [6-8]. This is part A of the processing pass. These methods usually employ a series of peeling and comparison operators as well as local logic operations to identify binary objects of specific sizes. These are directly applicable to this problem and can be used with little
modification. Fault type classification (part C) is not addressed in this paper because it is not essential for generation of an alarm signal. This would be necessary for a subsequent analysis of debris particles. We will focus directly on object type classification (part B).

4. Bubble/Debris Type Detection Based on Binary Morphology and Autowave Metric

The approach followed here is the filtering out air bubbles, using binary morphology [6,7] and autowave metric [9,10]. In the experiments we used binary images, the output of the field-programmed gate array that in the current system thresholds all gray-scale input images at a fixed level right after the acquisition. In a complementary study [18] we have investigated how the quality of these binary images can be improved by using a locally adaptive front-end filtering and segmentation strategy applied to the original gray-scale images.

4.1. Autowaves

The autowave approach has several advantages for pattern recognition [9,10]. Autowaves represent a particular class of nonlinear waves which spread in active media at the expense of the energy stored in the medium [11,12]. The properties of autowaves basically differ from those of waves in conservative systems, including nonlinear waves. The autowave, being a wave, can diffract and according to the Huygens’ principle, bypass obstacles. However, it has unusual properties as well. For example, two waves spreading in opposite directions do not pass through each other, as it is usual for waves, but mutually annihilate, similarly to particles. Autowaves in 2D 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, \( \frac{\partial u}{\partial t} \) is the rate of change of intensity values of the image \( u \). It is induced by \( f(u) \) plus the diffusion term \( D \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) \).

4.2. Classification algorithm

Classification is based on object-model comparison via difference measurement. A model is a set union of circles based on the hypothesis that an object is a group of one or more overlapping air bubbles. Figure 5 shows the flowchart of the bubble-debris classification algorithm containing Feature Extraction, Bubble Model generation, and Autowave Distance computation. The Feature Extraction block detects the center points of all objects and measures their sizes (Radii Map). These two characteristics are used for bubble model generation via autowave. Both features are extracted from a gray-scale image called Distance Map. This map is generated from the input image by using an operator similar that generates the Euclidean Distance Map. The brightness of each point of an object in the Distance Map encodes the distance to the nearest point in the background. The distance slightly depends on the measuring convention. The positions of local maximum values encode the center points of the objects (Center Points), while brightness values at local maximums encode the size of the objects to be modeled (Radii Map). The critical issue is to find the exact mass center of an object. In the case of multiple bubble groups, we need to obtain more than one center point. In
the next step, autowaves propagate from the center points and grow circles around them until the Radii Map stops this propagation. The autowave distance is computed between the bubble models and the input image in the third step. If the measured distance is large the object will be classified as a debris particle.

Figure 5 Flowchart of the bubble-debris classification algorithm.

Comparison of this algorithm to the one used at the NRL shows a stinking difference. This algorithm is classifies objects simultaneously in an image, in contrast to the other one in which each object is examined separately.

4.3. Employing the Autowave Metric

Below we discuss in detail how the autowave approach can be applied to the problem of 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 point sets. The Hamming distance (number of different points) is sensitive to image shift and presence of noise.

Another known distance metric is the Hausdorff metric which is more tolerant to shift [17]. The Hausdorff distance can be easily measured by using autowaves. Such measurement would require the generation of the trigger wave, whose initial position
coincides with one image. The wave propagates until all the points belonging to another image become triggered. The time required is equivalent to the asymmetric Hausdorff distance. To measure the Hausdorff distance, we should perform this operation twice with initial position coinciding with another image. The Hausdorff distance is extremely unstable in the presence of noise. The appearance of a noisy spot might drastically change the computed distance.

A variant of the Hausdorff metric called, autowave metric which has several advantages over Hausdorff metric, will be used in our experiments [10]. Let A and B be two objects to be compared. We consider the case when the compared sets A and B are partially overlapped closed contiguous regions. Let the wave spread only through the points belonging to the union of $A \cup B$, instead of spreading everywhere. The time required for the wave to occupy the union $A \cup B$ can be used to define the measure of the difference between two objects. To measure the asymmetric autowave difference $w_a(A, B)$, the initial position of the wave should coincide with A, and vice versa. The symmetric autowave distance $w_s(A, B)$ is given by

$$w_s(A, B) = \max (w_a(A, B), w_a(B, A))$$

The symmetric autowave distance has the following properties:

1. $w_s(A, B) = 0$ if and only if $A = B$
2. $w_s(A, B) = w_a(A \cap B, A \cup B)$

To measure the symmetric autowave difference the points belonging to the intersection of two point sets become the trigger points of the wave. (see Figure 6).

![Figure 6](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 time required to occupy the union can be used as a measure of the difference between A and B.)

The properties of the autowave distance provide increased tolerance to noise effects as opposed to the Hausdorff distance. For instance, if two images exactly coincide, except for only one outlying pixel, 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.

5. **Implementation of classification algorithm and autowave metric on CNN**

The details of the implementation can be found in [19]. Here only the main parts are discussed.
5.1. Implementing autowaves on CNN

Methods proposed for generating autowaves [9] can be realized on CNN architectures. Autowaves were observed in a CNN array having Chua’s circuits as cells [13,14]. In these experiments the nonlinear resistor of the chaotic oscillators provided the active local dynamics. Such a system can be built by using a simpler CNN architecture with the original cell-type [15,16]. There was a single-layer architecture in which the active local dynamics were generated with a delay-type template resulting in a bistable system.

The CNN dynamics can be described by the following equation

$$\frac{d}{dt} u_{ij}(t) = -\frac{1}{R \cdot C} \cdot u_{ij}(t) + \sum_s A_s \cdot g(u_{ij}(t)) + \sum_s \hat{A}_s \cdot (g(u_{ij}(t)) + \sum_s B_s \cdot v_{ij} + z_{ij}$$

where $u$ is the voltage level of a cell, $R$ and $C$ are the resistance and the capacitance of a cell. The $A$ and $\hat{A}$ describe linear and nonlinear interactions among the cells, respectively. $B$ denotes the feed-forward control determined by $v(.)$. $S$ determines the sphere of influence around a cell. The function $g(.)$ is a nonlinear output function and $z$ is a bias term.

By proper discretization of equation (1) we obtain:

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

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

The autowave equation can be directly mapped onto the CNN array ($S=1, R=1, C=1$) resulting in the following simple template

$$A = \begin{bmatrix} 0 & 0.25 & 0 \\ 0.25 & 0 & 0.25 \\ 0 & 0.25 & 0 \end{bmatrix}, \quad \hat{A} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & f(u) & 0 \\ 0 & 0 & 0 \end{bmatrix}. \quad B = [0], \; z = 0$$

Since we do not need the annihilation property of autowaves the focus will be put on the simplest type of autowaves, called traveling or trigger waves, where transition of the state of a cell can propagate in the system. We only need the conservation of amplitude during propagation. Thus, the term $f(u)$ can be:

$$f(u) = \begin{cases} 1.5 & \text{if } u > 0 \\ -0.6 & \text{otherwise} \end{cases}$$

The initial state should contain the trigger points of the autowaves. Although the $f(u)$ is the simplest nonlinearity applicable to trigger waves, it is still not available on the existing CNN chips. Advantage of this implementation is that the speed of the waves can be adjusted. Taking into account that present CNN chips do not support nonlinear interaction, we also specify a linear trigger wave generator template:
\[
A = \begin{bmatrix}
0.41 & 0.59 & 0.41 \\
0.59 & 2 & 0.59 \\
0.41 & 0.59 & 0.41
\end{bmatrix}, \quad B = \begin{bmatrix}
0
\end{bmatrix}, z = 4.5
\]

Given static binary image \( P \) and the initial state: \( X(0) = P \) (contains the trigger points of the waves). Although this linear template is a binary propagating type it does not belong to the class of the equation (1). Its advantage is the easy implementation and the fact that it can be tested on existing CNN chips.

5.2. Implementing feature extraction and bubble model generation on CNN

Two types of implementations can be considered. One of them operates using autowave approach and the other one needs only binary morphology operations. The first method results in the fastest solution but needs a sophisticated hardware with two-layer CNN structure. The second one is an iterative process, therefore it is slower but existing CNN chips support these operations.

The steps of the dynamic approach in a two-layer CNN structure are as follows. First a gray-scale map, called Distance Map, is constructed. The second layer will be filled with constant current and the voltage levels of cells will indicate the sizes of the corresponding objects. The constant current comes from the first layer where trigger waves continuously shrink the original objects. The local maxima of Distance Map encode the Center Points while cell values at these points are related to objects sizes (Radii Map).

The iterative approach is similar except that the shrinking of the objects and layer filling with a constant current are implemented with erosion operation and gray-scale addition among images through an iterative process.

The next step is the generation of bubble models. The center points of bubble groups are the initial points of trigger waves. The waves will spread from these points, producing larger and larger circles. It is necessary to constrain the propagation of the autowave. The Radii Map will be used to control this propagation.

The iterative implementation uses dilation operation to simulate trigger wave propagation.

5.3. Implementing autowave metric on CNN

The main task is to generate a map which contains values related to the difference between object pairs. This special map is called Wave Map and contains the autowave distances as maximal values in unions of objects and models for each object-model pair separately. Fig. 7 shows a possible implementation of the wave metric on CNN. The advantage of this two-layer implementation is that several object-model pairs can be compared at the same time.
Objects (P1)  
1-st layer

Objects (P2)  

2-nd layer

M = P1 OR P2  

Mask  

X[0] = P1 AND P2  

State  

X[0] = 0  

Wave Map  

Cell value = a*(Mask-State)*Time  

Average & Threshold
(Weighted Hamming)

Recall

Objects

Figure 7: Dynamic type 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.

Two images will be compared. One of them contains objects and the other one contains their models. The idea is that trigger waves will spread out from intersections of corresponding objects and models and time is measured while waves are occupying the unions of objects and models. The unions of sets are used as a mask to control the trigger waves enabling the propagation of waves only through the unions. The initial points of a trigger wave are the cells of the intersections of sets to be compared. While waves are propagating on the first layer, the second layer is filled with a constant current to measure time. The current has two components. One of them is determined by the mask, the other one comes from the output of the first layer. Due to the binary wave propagation the current is constant 2*a at a given cell (see Figure 7) iff the mask is black but the wave has not reached this position yet, otherwise it is zero. At the end of the process the cells at boundaries of the unions of objects and models will contain the highest voltage levels. Thresholding this image would give the autowave distance. Applying average and threshold operation, the wave metric equals to the weighted Hamming distance. Finally those objects might be recalled in which these differences are large indicating large difference.

Next, the iterative method for wave map generation is presented, see Figure 8. Its advantage is that it can be tested on existing CNN chips although it is a time consuming algorithm. The number of iterative steps depends on objects sizes to be compared.
Figure 8: Iterative type implementation of wave metric on CNN. From the intersections of sets to be compared, a binary morphology operation, namely dilation, enlarges objects width by one pixel in width in each step. The result of a step is used to fill a layer with constant current for a given time producing stairs like map. At the end of the process this will be the wave map.

6. Classification results

Here we present some results of applying this algorithm to real images. Figure 9 shows consecutive steps of bubble-debris classification algorithm. The gray-scale input picture contains three debris particles the remaining objects are all bubbles. Although some bubbles are connected to each other the algorithm can recognize that these are not debris particles. However, further examinations are necessary to tune the algorithm to achieve the desired robustness in order to implement on a real CNN chip and fulfill the requirement of very low false alarm rate.
We have trained and tested the performance of the algorithm on two different image sequences containing fifty images, respectively. The size of the images was 128x128. The total number of objects was between 2500-2600 and there were 130-150 debris objects. Each image contained approximately 40-50 objects with 2-3 debris particles. Figure 10 shows some examples.

The power of the proposed algorithm was analyzed by constructing ROC (Response Operating Characteristic) shown in Figure 11. The false alarm rate was computed as the ratio of false classifications and the total number of objects. The true positive values were constructed as the ratio of detected debris particles and the total number of debris particles. Although the ratio of the classification of debris particles is relatively high and the false alarm rate is low, further improvement of several orders of magnitude is still needed.
The reason for proposing the autowave metric to solve this classification problem is the following. Relying on autowave distance calculation a qualitatively better solutions can be derived compared to different variants of the Hamming metrics. Furthermore, though it is computationally expensive, the CNN hardware ensures an efficient execution. In the CNN framework to compute the weighted Hamming distance needed for classification the number of detected points should be normalized with reference to the object’s area. This means that we cannot define a global threshold level and each object should be separately examined. The implemented autowave metric measures differences between objects and their models, converting the CNN transient length to a corresponding gray-scale level. In this case a global threshold level can be used for all objects in the classification step.

7. Conclusions

We have presented a possible solution for the bubble-debris classification problem, where the major requirement is real-time processing with a very low false alarm rate for miss-classified bubbles. Initial results show the CNN processor with the autowave metric can distinguish bubbles and debris particles and has the potential for high speed classification. Further analysis is necessary to test the sensitivity and robustness of the synthesized algorithm and to improve the false alarm rate to a level needed for this application.

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9. References


Biographies - Bubble-debris classification via binary morphology and autowave metric on CNN

István Szatmári received the M.Sc. degree in electrical engineering from the Technical University of Budapest, Budapest, Hungary, in 1995. He is now a Research Engineer at the Analogical and Neural Computing Research Laboratory at the Computer and Automation Institute, Hungarian Academy of Sciences, where he deals with cellular neural-nonlinear networks (CNN’s). From January 1997 he spent eight months at University of California (Berkeley, USA) as a research assistant working on CNN projects related to real time image processing. He is currently working toward the Ph.D. degree. His research interests include associative memories, theory of metrics, and hardware design hosting CNN-UM chips.

Abraham Schultz received his B. S. degree in physics from the University of Delaware, the M. S. degree in physics from the University of Maryland, and the Ph. D. in mathematics from the University of Maryland. He joined the Naval Research Laboratory in 1971 and initially worked in the area of military operations research and ocean surveillance. Since 1986 he has been engaged in basic and applied research. He spent two years doing research on ionospheric radio wave propagation. For the past several years his research interests have been in the areas of neural networks, pattern recognition, and computer vision.

Csaba Rekeczky received the M.S. and Ph.D. degrees in electrical engineering from Technical University of Budapest in 1993 and 1999, respectively. He is currently at the Analogical and Neural Computing Systems Laboratory of the Computer and Automation Institute of the Hungarian Academy of Sciences. From May 1994 to May 1995 he spent a year at Tokushima University (Tokushima, Japan) as a research assistant working on CNN projects related to medical image processing. From May 1997 to May 1998 he was working on nonlinear image processing and neuromorphic CNN modeling of the vertebrate retina at University of California (Berkeley, USA). His research interest is mainly focused on computational aspects of cellular nonlinear arrays and includes early vision techniques, nonlinear adaptive filtering, target tracking, image segmentation and neuromorphic modeling. His IEEE membership number is 41250661.

Tibor Kozek received the MS degree in electrical engineering from the Technical University of Budapest in 1992 and the Ph.D. degree from the Hungarian Academy of Sciences in 1997. He has been a visiting scholar, GRE, and a postdoctoral research
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Tamás Roska (M’87-SM-90-F’93) received the Diploma in electrical engineering from the Technical University of Budapest, Budapest, Hungary, in 1964 and the Ph.D. and D.Sc. degrees in 1973 and 1982, respectively.

From 1964 to 1970 he was with the Measuring Instrument Research Institute, Budapest. From 1970 to 1982 he was with the Research Institute for Telecommunication, Budapest. Since 1982 he has been with the Computer and Automation Institute of the Hungarian Academy of Sciences, where he is Head of the Analogic and Neural Computing Research Laboratory. Since 1989 he has been a Visiting Scholar at the Department of Electrical Engineering and Computer Sciences and the Electronics Research Laboratory and was recently a Visiting Research Professor at the Vision Research Laboratory of the University of California at Berkeley.

His main research areas are cellular neural networks, nonlinear circuits and systems, and analogic spatiotemporal supercomputing.

Since 1975 he has been a member of the Technical Committee on Nonlinear Circuits and Systems of the IEEE Circuits and Systems Society. Recently, he has served twice as Associate Editor of the IEEE Transactions on Circuits and Systems. He received the IEEE Fellow Award for contributions to the qualitative theory of nonlinear circuits and the theory and design of programmable cellular neural networks. In 1993 he was elected a Member of the Academia Europaea (European Academy of Sciences, London) and the Hungarian Academy of Sciences. In 1999 he became the Founding Chair of the Technical Committee on Cellular Neural Networks and Array Computing of the IEEE Circuits and Systems Society. His IEEE membership number is 08547077.

Leon O. Chua – is currently a Professor of electrical engineering and computer sciences at the University of California, Berkeley. His research interests are in the areas of general nonlinear network and system theory. He has been a consultant to various electronic industries in the areas of nonlinear network analysis, modeling, and computer-aided design. He is the author of Introduction to Nonlinear Network Theory (McGraw-Hill, 1969), Cellular Neural Networks: a