COMPUTING ON SILICON WITH TRIGGER WAVES: EXPERIMENTS ON CNN-UM CHIPS

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ABSTRACT

In this paper, experimental results on Cellular Neural Network Universal Machine (CNN-UM, [1]-[4]) chips will be presented. These analogic spatio-temporal visual microprocessors make it possible that one can use nonlinear waves as the basic kernels of algorithms solving filtering-reconstruction and/or detection-classification problems. Showing output results from series of experiments it will be demonstrated how trigger waves, the simplest nonlinear waves, can constructively be used in a number of important application areas.

1. INTRODUCTION

In recent years, a number of theoretical studies were presented (e.g. [8]-[10]) discussing various wave-computing techniques. All these methodologies, including the PDE-based approaches, require an ultrafast computing device in order to be used in real-time applications. In previous studies ([16]-[17], [22]), it has been shown that even simple trigger-waves, when implemented on a parallel nonlinear device, can be a very powerful tool at the core of complex algorithms. In this study, it will be demonstrated that analogic CNN visual microprocessors, designed in the CNN-UM framework (e.g. [5]-[7]), are dedicated hardware for wave-type computation. We will focus on two typical problem classes: (i) rigid and non-rigid object shape detection and tracking with active contour methods, and (ii) object classification based on nonlinear wave metric. Both of these methodologies will use trigger-waves as the basic computing tool running on a CNN-UM chip [7].

2. ACTIVE CONTOUR METHODS

A *trigger-wave*, is a binary wave that expands or shrinks along the boundary of two regions being in opposing state (in CNN literature black represents +1 and white stands for -1). The evolution of a trigger-wave front can be described by two synonyms. In some context, when the focus is put on the transformation of local morphologies, the moving boundary is

referred to as an *evolving interface* (see also Sethian [10]). By definition, the boundary of the black region is called an *active contour*, putting the emphasis on phenomena that the shape of a region is changing in time. This is a meaningful interpretation approaching shape detection/recovery problems. However, we would like to note that here the active contour terminology is not used exactly in the sense of the original definitions by Kass *etc.* [8] (see a corresponding discrete-time CNN approach in [15]), i.e. as a deformation due to internal and external energies. The approach is rather a *local analysis* of the ODE system, i.e. looking at the control and feedback mechanisms directly determined by the connection weights in a CNN template, when examining the continuous evolution of a wave-front. The design and analysis has been performed in both time and frequency domain building also on results reported in [11]-[14].

2.1 Basic Techniques

Two basic techniques will be shown: (i) simple trigger-wave generation and control (Fig. 1-2), (ii) reconstruction/recall of binary objects from markers by trigger-waves (Fig. 3). Both these methods represent a computation by a single CNN transient and are the key elementary template operations of trigger-wave based analogic CNN algorithms.

Figure 1 Trigger-wave generation from different initial conditions. Top row: simple objects given as initial conditions, bottom row: patches created by trigger-wave propagation.

Figure 2 Trigger-wave generation from initial patches: a snapshot of the expanding wave-front.

Figure 3 Recall/reconstruct implemented based on trigger-waves. (a) input image: a set of binary objects, (b) markers, (c) the output of the recall/reconstruct operation: labelled objects are reconstructed.

2.2 Non-rigid Object Tracking

A typical non-rigid shape detection problem is offered by ultrasound echocardiography: tracking the boundary of the left ventricle in space and time in a sequence of ultrasound images. This important task is solved on a "video-flow" of the echocardiography machine. 25 typical frames (resolution: 64x64) of the left ventricle are shown bellow (Fig. 4) - supplied as the input of the CNN Universal chip. The processing results are visualized by superimposing the extracted contours onto the original images. Processing a frame takes about 250 μ sec (measured result on a 64x64 CNN Universal Machine chip, no loading type included). For comparative analysis both the simulated and the on-chip results are given.

Simulation:

On-chip:

Figure 4 Non-rigid object tracking: tracking the boundary of the left ventricle in ultrasound echocardiography (both simulated and on-chip results are shown).

2.3 Rigid Object Tracking and Fusion

Target tracking in a real scene usually belongs to rigid object tracking problems. These types of experiments are shown in the next example where target tracking is combined with image fusion on daylight and IR camera inputs (Fig. 5).

Figure 5 Rigid object tracking combined with fusion on daylight and IR camera inputs. (a) daylight camera input, (b) IR camera input, (c) fusion result, (d) fusion combined with tracking.

2.4 Solving the Shortest Path Problem by Trigger-waves

Skeletonization can be generalized [17] to solve the shortest path problem in a narrow flat labyrinth, an approach different than some previous algorithms based on “back-tracking” approaches. The solution is obtained through three computational phases: (i) exploration, (ii) skeletonization, and (iii) pruning. Under mild conditions all processing blocks can be replaced by a trigger-wave based solution. Fig. 6 gives an example for on-chip experiments implemented on the 64x64 CNN-UM chip.

Figure 6 Intermediate results of the shortest path algorithm containing trigger-wave based solutions: (a) input image: binary labyrinth, (b) the output of the exploration phase, (c) skeletonization result, (d) the shortest path obtained after pruning away all branches by another trigger-wave generating template.

3. WAVE METRICS

When the image processing task is to compare different objects in a scene, the chosen distance calculation methodology plays an important role in the algorithm design. There are several methods

Figure 7 Wave Map generation implementing the kernel of the nonlinear wave metric. a) Outlines of two partially overlapping point sets, b) Trigger wave spreads from the intersection through the union of the contiguous part of point sets until all the points become triggered, c) Wave map generated by increasing intensities of pixels until trigger wave reaches them, simulation result d) Consecutive steps of generating the Wave Map on the 64x64 I/O CNN-UM chip.

that can all be viewed as efficient techniques for object classification or recognition via comparison with prototypes (pattern matching). For distance measurement the choice of a metric is a nontrivial problem since it is easy to give examples when well-known distance measures, such as Hamming, Hausdorff, and Nonlinear Hausdorff [18]-[20] metrics, are completely inadequate for classification [21].

This has led us to a generalized approach, based on nonlinear wave-type computation, in which previous metrics are included as special cases [21]. In this new methodology a trigger-wave based spatio-temporal process explores the objects and the dynamics during the evolution is recorded and stored in a so-called Wave Map. From this map several simple metrics can be derived along with more sophisticated ones that make it possible to classify objects in a number of non-trivial cases.

Here, we only show the output of the kernel (Wave Map construction) of the wave metric algorithm implemented on a currently available CNN-UM chip (Fig. 7).

4. SUMMARY

We have presented the first experimental results dealing with stored-program wave-type computation on CNN-UM chips. Trigger-waves were *generated* and *controlled* on silicon thereby used as flexible computing tools building up the kernels of algorithms solving detection and/or classification problems.

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