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Processing Large-Scale Images on Ace16k Using Discrete Wavelet Transform

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Abstract: *Image processing has crucial effects in many fields like biomedical applications, traffic control, security, satellite systems and so on. Because of its improving importance, various methods are proposed for increasing computation speed and reliability. Cellular Neural Networks - Universal Machine (CNN-UM) is a promising hardware implementation for generating rapid results. In this study, we have implemented discrete wavelet transform (DWT) on input images in order to improve accuracy of edge detection applications on ACE16k which is one of the analog processors handling 128x128 images. Besides, DWT gave us an opportunity to process large-scale images. At the end of the study it is shown that DWT provides appreciable contribution to edge detection results.*

Keywords: *CNNs, ACE16k, Discrete Wavelet Transform, Edge Detection, Iterative Annealing*.

1. Introduction

As a fundamental concept in image processing, edge detection, is a popular study area. Therefore, many studies using various algorithms were performed. In some of those, a well-known signal processing method called wavelet transform that reveals the details in horizontal, vertical and diagonal directions in the input image is used as a preprocessing step. For instance, Madchakham et al. used multiscale edge detection on SAR images, after producing highpass subbands in order to eliminate noise [1]. In a similar study, Pan et al. also used wavelet transformation for noise elimination and implemented edge detection by Canny algorithm [2]. Yu et al. applied 2-D Haar wavelet transform and following edge detection process on a simulated Cellular Neural Networks (CNNs) [3].

A CNN is a type of neural networks in that every cell is in interaction with only its *r*-neighborhood. This property is called locally interconnection which reduces computational complexity. The other important property of CNNs is usage of analog processing cells with continuous signals [4] [5]. Furthermore, it is preferable for image processing applications due to its two dimensional (2D) grid structure. In order to implement CNNs not only in software but also in hardware, a programmable type called CNN-Universal Machine (CNN-UM) was developed [6].

In this study, edge detection templates established in [7] with Iterative Annealing Optimization Method (IAOM) [8] are used on ACE16k which is a CNN-UM implementation. Prior to detection step, a Daubechies wavelet (DB1) [9] is applied on input image in order to enhance the accuracy of results.

This study is organized as follows. The main structure of CNN-UM, Bi-i Cellular Vision System, a chip specific optimization method Iterative Annealing, the templates generated by IAOM and used for edge detection are explained in section 2. Section 3 is about discrete wavelet transform which we applied as a preprocessing step. Subsequently, experimental results are given in section 4. Finally, assesments regarding to our findings are indicated in section 5.

2. CNNs and bi-i cellular vision system

2.1. Architecture of CNNs

A standard CNN consists of *MxN* rectangular array of cells. The smallest part of CNN is called cell

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C(i,j) with Cartesian coordinates *(i,j)* *(i=1,2,3...M, j=1,2,3...N)*. Each cell can be defined by the following linear and non-linear mathematical equations [10];

$$C\frac{dx_{ij}(t)}{dt} = -\frac{1}{R_x}x_{ij}(t) + \sum_{C(k,l)\in S(i,j)} A(i,j;k,l)y_{kl}(t) + \sum_{C(k,l)\in S(i,j)} B(i,j;k,l)u_{kl} + I_{ij}$$

$$y_{ij} = f(x_{ij}) = \frac{1}{2}\left(\left|x_{ij}+1\right| - \left|x_{ij}-1\right|\right) \qquad (1)$$

where,
C ; a linear capacitor,
R_x ; a resistance,
x_{ij} n R ; State variable of cell *C(i,j)*,
y_{kl} in R ;Outputs of cells,
u_{kl} in R ; Inputs of cells,
I ; Threshold,
A(i, j ; k, l) ; Feedback operator,
B(i, j ; k, l) ; Control operator,
y_{ij} ; Output equation.

The sphere of influence, $S_r(i,j)$, of the radius r of cell *C(i,j)* is defined to be set of all neighborhood cells satisfying the property

$$S_r(i,j) = \left\{ C(k,l) \,\middle|\, \max_{1\le k\le M,1\le l\le N} \{|k-i|,|l-j|\} \le r \right\} \qquad (2)$$

The total number of the template parameters in a CNN is 19 when $r=1$ (a threshold parameter I, 9 parameters a_{kl}, 9 parameters b_{kl}). The general structure of the CNN templates is as follows

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \ \mathrm{B} = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \text{and} \quad \mathrm{I}$$

2.2. Bi-i cellular vision system

The Bi-i cellular vision system which contains ACE16k chip and Digital Signal Processor (DSP) is a high-speed, compact and intelligent camera for image acquisition. Programs to be run on Bi-i are loaded to host computer over Ethernet allowing data transfer. For this system, Instant Vision Libraries and Bi-i SDK (Software Development Kit) which are sets of C++ programming library are used for application development. These libraries can be used for the DSP and ACE16k with the development environment called Code Composer Studio. Functions in the SDK are operations on different components of the Bi-i hardware such as operating the CMOS sensor. TACE_IPL library is an image processing library for ACE16k chip [11] [12].

2.3. ACE16k chip

ACE16k is an implementation of CNN-UM which is an analog and logic computer that consists of many interconnected parallel processor units on its main processor. ACE16K has an array of 128x128 identical, locally interacting, analog processing units designed for high speed image processing tasks. It computes in analog in domain but can be operated in a fully digital environment [13]. Images can be acquired either by chip specific optical input module or by a digital hosting system.

2.4. Edge detection on ace16k

In a previous study, we have developed a template training system for ACE16k chip in Bi-i Cellular Vision System. In this system, we have used a CNN specific optimization method called Iterative Annealing for training procedure. This system can be applied to various template training problems. We have established gray-level edge and corner detection templates and some other applications using this system [7]. In this paper, we also add wavelet transform to gray-level edge detection procedure. The template which is used for this purpose is shown below.

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 3.2 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \ \mathrm{B} = \begin{bmatrix} -3 & 1.94 & -1.55 \\ 0.64 & 5.88 & -0.51 \\ -1.79 & -0.02 & -1.77 \end{bmatrix}, \ \mathrm{I} = -0.8$$

3. Discrete wavelet transform

Discrete Wavelet Transform (DWT) is a well-known methodology to represent a signal as a set of oscillations called Wavelets. DWT has been used in many study areas like image processing, cardiac signal processing, acoustic signal monitoring etc. with various wavelet filters such as Haar, Discrete Meyer and most common Daubechies wavelets [9].

For one-level of DWT in image processing applications, input image I^0 is passed through one of a low pass (scaling function - G) or a high pass filter (wavelet function - H) in both vertical and horizontal directions in order to produce one of four sub-bands I^1, S_2^1, S_1^1, S_0^1. In this study, DB1 (Daub1) wavelet is used for two dimensional DWT. Low pass and high pass filters for DB1 are $G = [1/\sqrt{2} \;\; 1/\sqrt{2}]$, $H = [-1/\sqrt{2} \;\; 1/\sqrt{2}]$, respectively.

Resulting images are downscaled to half of input image size. Entire process can be seen in Figure 1.

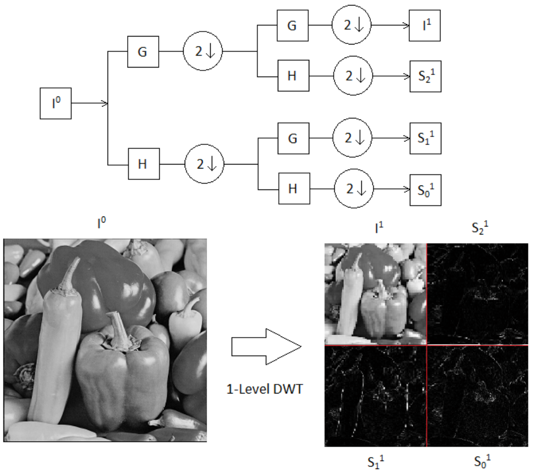

Figure 1. Single level DWT of input image I^0 and corresponding sub-bands.

As seen in Figure 1, S_2^1, S_1^1 and S_0^1 shows horizontal, vertical and diagonal details in input image, respectively. I^1 is the approximation at level 1. For repetitive DWT iterations, approximation at each level (I^N) is chosen as input image.

4. Experimental results

We have implemented our gray-level edge detection template with and without wavelet transform on some sample images of Lenna and Peppers. For the implementation with DWT transform, we have applied our edge detection templates on each of sub-bands that had been derived from input image. In the following step, OR operation has been used to generate output. All implementations were run on ACE16k. Besides, we have used different sized (256x256 and 512x512 pixels) images. Subsequently, the comparisons of the outputs in order to show the contribution of wavelet transform have been presented.

Original Lenna image (256x256), edge detection result with and without DWT are given in Figure 2a, Figure 2b, Figure 2c, respectively.

As a different image, original peppers (256x256) and corresponding outputs are also given in Figure 3a, Figure 3b, Figure 3c.

As seen in Figure 2b and Figure 3b, edge detection outputs of DWT applied images contain much more details than outputs of non-DWT images (Figure 2c and Fig 3c).

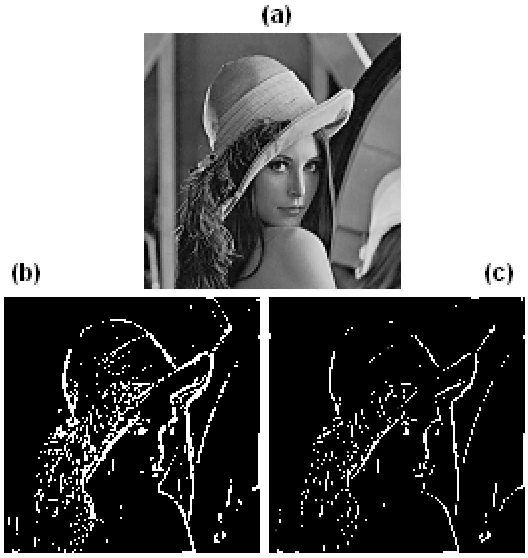

Figure 2. Edge detection results for Lenna a) Original image b) Result with DWT c)Result without DWT.

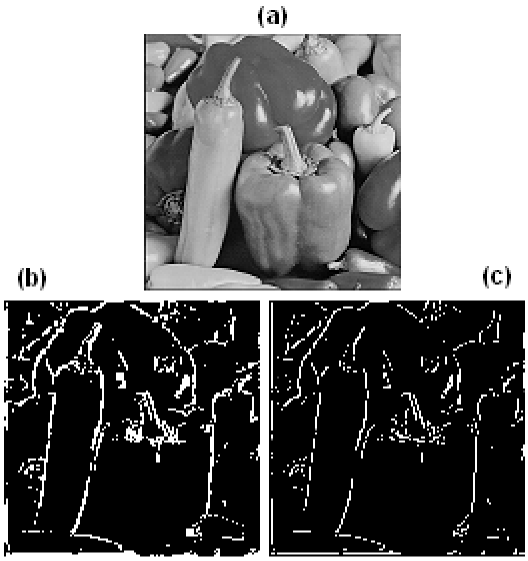

Figure 3. Edge detection results for peppers a) Original image b) Result with DWT c)Result without DWT

In order to experiment the effect of multi-level DWT on edge detection, we have also used 512x512 sized peppers image. Minor difference between results (Figure 4a and Figure 4b) is observed.

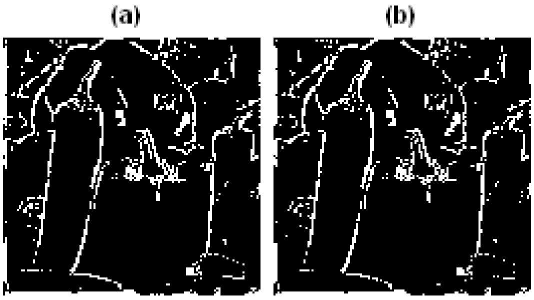

Figure 4. Edge detection results after a) 1-level DWT b) 2-level DWT

5. Conclusions

ACE16k chip in Bi-i Cellular Vision System is a powerful real-time CNN-UM which has a wide range of usage in image processing applications. Nevertheless, one of the major disadvantages of ACE16k is its limitation in input/output image size (128x128 pixels). Hence, images exceeding this size need to be down scaled. N-level DWT is an appropriate method for this task. We have shown this case by applying 2-level and 1-level DWT on 512x512 and 256x256 sized images, respectively.

DWT generates four sub-bands of an input image consisting of horizontal, vertical, diagonal details and approximation. By this way, in fundamental image processing applications like edge detection one can obtain more accurate results. We have shown this contribution of DWT on our sample images in Figure 2 and Figure 3. Also as seen in Figure 4 no significant difference between edge detection results of 1-level and 2-level DWT are found.

6. References

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