Cellular Neural/Nonlinear Networks for Identification of Infant Retinal Defects

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***Abstract*— In this paper, Cellular Neural/Nonlinear Network (CNN) based image processing and its application in the diagnosis of Retinopathy of Prematurity (ROP) is detailed. By processing retinal images of prematurely born infants, a proposed device that is both inexpensive and portable can aid ophthalmologists in identifying symptoms of Plus Disease and diagnosing ROP.**

I. Introduction

Cellular Neural/Nonlinear Networks (CNNs) are comprised of cellular processing units, or cells, that are locally connected to neighboring cells. The specific CNN template applied to the system defines how the state of a central cell interacts with the states of its neighboring cells. This provides a massively parallel architecture consisting of many multiple input single output (MISO) processors capable of large scale analysis of fields of data. With this in mind, CNNs are ideal for applications in image processing as the pixels of an image are directly analogous to the cells of CNNs.

In this paper, the use of CNNs for image processing is applied to an area of ophthalmology, the branch of medicine that specializes in the anatomy, physiology, and diseases of the eye. Specifically, this paper proposes an innovative approach to the diagnosis of Retinopathy of Prematurity (ROP). ROP is a disease of the retina that occurs in prematurely born infants, and if left untreated, can lead to partial or even complete detachment of the retina. It is a major cause of blindness in children around the world and is becoming increasingly prevalent in developing countries, where rates of premature births are increasing [1]. In order to diagnose ROP, medical experts examine photographs taken of an infant's retina. The current option for such diagnosis is an expensive and non-portable device that does not allow for easy access to premature infants born in developing regions. This paper describes a proposed alternative that offers an inexpensive and portable system that is also capable of CNN image processing.

II. CNN Image Processing

A. CNN Templates

Individually, pixels of an image have little meaning since they only have a single value that represents a small part of the whole image. Observing pixels in groups, however, provides a better representation of what is being displayed. Therefore, by analyzing these groups, also called neighborhoods [2], a CNN image processor can detect features of an input image. The features that the CNN detects are defined in the template being applied. Templates set the parameters that the analysis operates under and defines how to process neighborhoods.

One such CNN template is called threshold. Effectively, the threshold template allows the user to define a pass/fail threshold for the grayscale value of neighborhoods of pixels. In 8-bit grayscale images, there are 256 unique shades of gray ranging from 0, which is black, to 255, which is white. The threshold can range from -1.0 to +1.0 and its value determines a boundary that separates pixels into two categories: pixels that are lighter than the threshold and pixels that are darker than the threshold. The template then interprets the image based on this division in that the lighter pixels become white and darker pixels become black. As a result, the output of the image processing is a binary image that highlights features based on grayscale intensity.

In CNN image processing, a function such as threshold may be simple, but when applied to the diagnosis of ROP, it becomes very powerful. In order to understand the practicality of the threshold template, the causes and symptoms of ROP must first be understood.

B. Applications in ROP Diagnosis

In human fetuses, retinal vascularization begins in the fourth month of pregnancy. These blood vessels slowly progress radially from the optic nerve until it reaches the edge of the retina just before birth [1]. This means that the retinas of premature infants have underdeveloped vascular structures. After birth, it is critical that premature infants are taken to a neonatal intensive care unit and put into a high oxygen environment where underdeveloped lungs can more effectively absorb oxygen. While this is necessary for most preterm infants, it comes with certain risks. Prolonged exposure to high concentrations of oxygen can lead to hyperoxia, a condition in which body tissues have an excess of oxygen. Past studies have shown a strong relationship between hyperoxia and the development of severe ROP [3]. The high levels of oxygen cause blood vessels to dilate to abnormal diameters. This condition is known as Plus Disease, and is a key indicator of advanced stage ROP that requires treatment [4]. Plus Disease can cause bleeding of the retina, which leads to a buildup of scar tissue, which, in turn, can push the retina away from the inner wall of the eye. In examinations of preterm infants, ophthalmologists look for signs of Plus Disease in order to determine the risk and severity of ROP.

In this sense, CNN image processing has the potential to play a significant role in the diagnosis of ROP. By helping medical experts identify features such as enlarged blood vessels, CNN image processors can increase efficiency and accuracy of diagnoses [5]. In Fig. 1, the threshold template from the simulation tool MatCNN is shown, refer to Sections III and IV for more information on MatCNN. The figure also displays the input (top) and output (bottom) images of a simulation that applied the threshold template to a grayscale image of a model retina (top). The threshold value, set by *THRES_I,* was chosen in order to differentiate the blood vessels from the surrounding tissue.

```
THRES_A = [0 0 0;
           0 2 0;
           0 0 0];
THRES_I = -.6156;
```

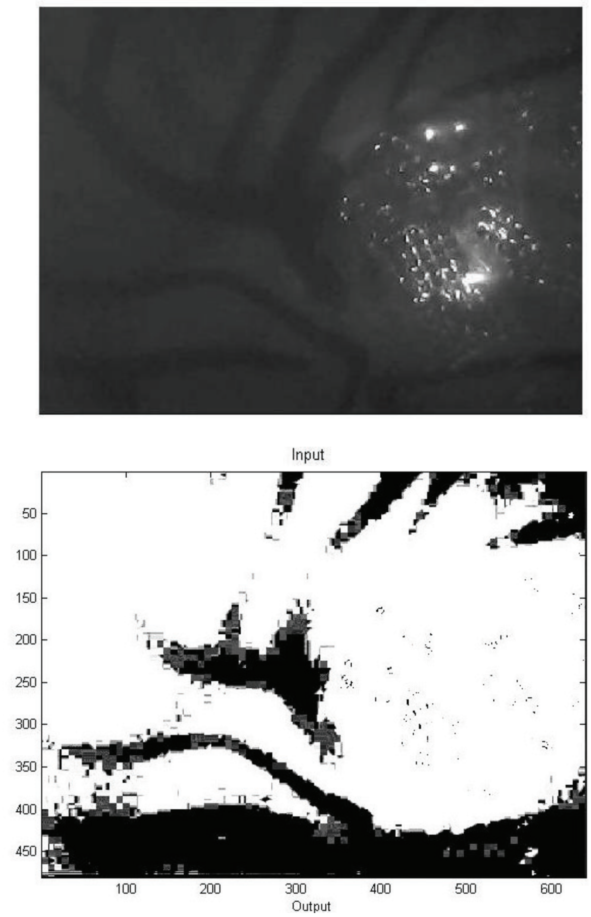

Fig. 1 Threshold CNN template used by *MatCNN*. THRES_A defines the neighborhood feedback, and THRES_I defines the threshold value. The top image is a grayscale photo of a model retina that displays signs of ROP. The bottom image is the output from the MatCNN simulation using the threshold template. As shown, the blood vessels were successfully differentiated from their surroundings.

As seen in Fig. 1, CNN image processing has huge potential. Even with a very dark input image, the CNN simulator was able to identify the vascular structures and eliminate the surrounding tissue. It is noteworthy to mention that the simulator was also able to discern the difference between the enlarged blood vessels and the normal blood vessels. This can be attributed to the neighborhoods of pixels that the CNN template analyzed. In the image, the larger blood vessels had larger, more coherent neighborhoods, whereas the smaller blood vessels had smaller neighborhoods that were harder to distinguish from their surroundings. Therefore, the larger blood vessels could withstand more iterations of the template than the smaller blood vessels and their surroundings could. This created an output image that clearly displayed the enlarged vascular structures of the model, which is the characteristic most associated with Plus Disease and ROP [6]. Thus, this paper is proposing a CNN based image processor that uses this in order to offer an inexpensive and portable method of diagnosing ROP.

III. CNN SIMULATION USING MATCNN

A. MatCNN for Image Processing

In order to grasp the advantages and the practicality of image processing through CNNs, simulations were performed using MatCNN, a CNN toolbox for Matlab. Developed by Eutecus, Inc., MatCNN provided a library of CNN templates through which grayscale bitmap (.bmp) images could be processed [7]. Edge detection, enhance edges, diffusion, and threshold are just a few of the many templates provided. When simulating, MatCNN allowed for multiple templates to run sequentially and for individual templates to be customized, which demonstrated the seemingly limitless potential that CNN based image processing possesses.

To begin implementing MatCNN in Matlab, a script file was written to define the CNN environment and to initialize multiple variables that determined the settings of the simulations. In order to optimize the accuracy and clarity of the simulation output images, the time step of the simulation was set to 0.1 and the number of template iterations in the simulation was set to 50. These two values ensured that the MatCNN simulation conducted was both thorough and that each individual iteration was done in a reasonable amount of time. After selecting these settings for the simulation, the input JPEG image was converted to double precision and then from a color image to a grayscale image. Due to the format of the MatCNN simulation functions, this grayscale image also had to be converted to a CNN compatible image by utilizing a MatCNN conversion function. Once the formatting was completed, the simulation was ready to begin.

B. MatCNN Results and Proof of Concept

To further understand the capabilities of the MatCNN toolbox, several templates were simulated in different sequences. This was done to help determine which templates would be most effective in diagnosing various symptoms of ROP, most notably Plus Disease, which is characterized by dilated retinal blood vessels.

The first template in the image simulation was an enhanced edge simulation (ENHEDGE), which was used to define edges and add sharpness to the image being processed. This helped with distinguishing objects and shapes in the image, such as individual blood vessels. Although the enhanced edge template assisted with defining the outlines of shapes in the image, a second template for edge detection (EDGE) was used to further define and enhance the edges in the simulated image. This resulted in an even sharper and more detailed image.

Following the two different edge templates, a threshold simulation template (THRES) was used to separate the blood vessels from their surroundings by

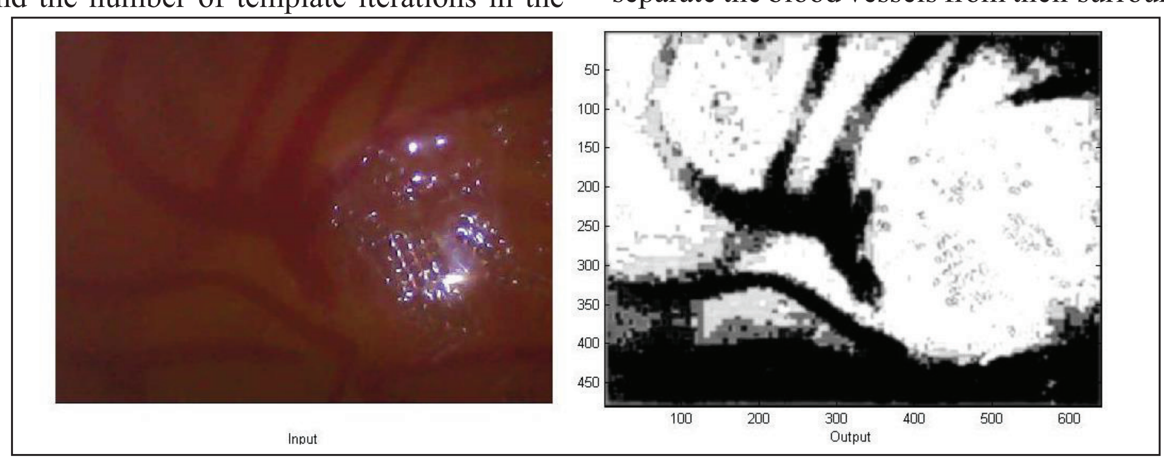

Fig. 2 Final results from the MatCNN simulation. The simulation processed the JPEG image of a model retina (left) through the series of templates described in Section III Subsection B and resulted in the image on the right.

removing excess shapes. Refer to Section II for more details. This template made it easier to detect larger blood vessels and to distinguish them from smaller ones.

The final template that was utilized was a diffuse template (DIFFUS). This template helped improve the general quality of the image by refining the blood vessels, making them stand out more, and diminish any anomalies in the output image, including possible glares from the camera and any noise from the previous templates.

The final results of this simulation can be seen in Fig. 2 and serve as a proof of concept for the design proposed in Section IV.

IV. PROPOSED ALTERNATIVE

As displayed in Fig. 2, the use of CNNs for image processing is very effective at isolating the blood vessels of the retina, especially those that are enlarged. Therefore, CNNs have great potential in aiding ophthalmologists in identifying symptoms of Plus Disease and diagnosing ROP. One of the only options for diagnosis is an expensive and non-portable device that many developing regions do not have access to. This paper proposes a low-cost, portable alternative to diagnosing ROP that uses CNNs as the method of detecting abnormalities in the retina. A block diagram of the design is shown in Fig. 3.

The platform for the proposed design is the DE1-SoC, which is comprised of a Cyclone V FPGA with a dual-core ARM Cortex-A9 microprocessor (HPS) [8]. The HPS will run the Linux 3.7 Kernel, which includes a Linux USB Driver that allows for the microprocessor to communicate to the USB camera. When a picture is taken by the USB camera, the Linux Kernel activates the CNN, which uses the captured image as an input for the CNN image processing that occurs on the FPGA. After the image is manipulated with the CNN to detect symptoms of ROP, the image is sent back to the ARM microprocessor. Finally, the Linux Kernel sends the image to the VGA Core on the FPGA, which allows the final processed image to be displayed to the user. Due to the smaller size and simplicity of this design, the device would be a portable unit that is inexpensive and easily accessible.

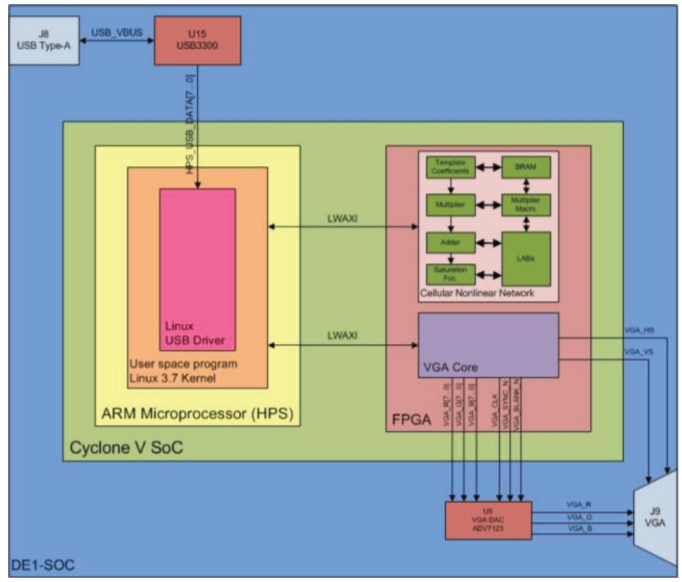

Fig. 3 The block diagram for realizing an FPGA-SoC based CNN image processor to be used for the diagnosis of ROP.

The completed design will be presented at ISCAS 2015, along with the results obtained from testing. Reference designs, presentation PDFs and other material related to this project can be found on our project website [9].

ACKNOWLEDGMENT

Special thanks to Dr. Bharathwaj Muthuswamy. This project would not have been possible without his guidance and support.

REFERENCES

[1] J. Chen, and L. E. H. Smith. Retinopathy of prematurity. *Angiogenesis* 2007; vol. 10, issue 2; pp. 133-140.

[2] L. O. Chua, and L. Yang. Cellular neural networks: theory. *IEEE Transactions on Circuits and Systems* 1988; vol. 35; pp. 1257-1290.

[3] C. Deuber, and M. Terhaar. Hyperoxia in very preterm infants: a systematic reivew of the literature. *The Journal of Perinatal & Neonatal Nursing* 2011; 25(3): 268-274.

[4] M. F. Chiang, L. Jiang, R. Gelman, Y. E. Du, and J. T. Flynn. Interexpert agreement of plus disease diagnosis in retinopathy of prematurity. *Arch Ophthalmol* 2007; 125(7): 875-880.

[5] A. Anzalone, F. Bizzarri, M. Parodi, and M. Storace. A CNN for biomedical image processing. *Proceedings of the 2005 Conference on Circuit Theory and Design* 2005; vol. 3; pp. 169-172.

[6] Facts about retinopathy of prematurity (ROP) 2014. National Eye Institute, National Institutes of Health, United States Department of Health and Human Services.

[7] Cs. Rekeczky. MATCNN-Analogic Simulation Toolbox for Matlab. *Analogic and Neural Computing Laboratory, Computer and Automation Institute* 1997.

[8] DE1-SoC User Manual. 2014. Terasic Technologies Inc.

[9] http://www.harpgroup.org/OpenCLCNN/InfantRetinalDefectIdentification/