

# Stream Processing of a Neural Classifier II

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## INTRODUCTION

This article presents a real-time Fuzzy ART neural classifier for skin segmentation implemented on a *Graphics Processing Unit* (GPU). GPUs have evolved into powerful programmable processors, becoming increasingly used in time-dependent research fields such as dynamics simulation, database management, computer vision or image processing. GPUs are designed following a *Stream Processing Model* and each new generation of commodity graphics cards incorporates rather more powerful and flexible GPUs (Owens, 2005).

In the last years *General Purpose GPU* (GPGPU) computing has established as a well-accepted application acceleration technique. The GPGPU phenomenon belongs to larger research areas: *homogeneous and heterogenous multi-core computing*. Research in these fields is driven by factors as the *Moore's Gap*. Today's uni-processors follow a 90/100 rule, where 90 percent of the processor is passive and 10 percent is doing active work. By contrast, multi-core processors try to follow the same general rule but with 10 percent passive and 90 percent active processors when working at full throughput. Single processor *Central Processing Units* (CPUs) were designed for executing general purpose programs comprised of sequential instructions operating on single data. Designers tried to optimize complex control requirements with minimum latency, thus many transistors in the chip are devoted to branch prediction, out of order execution and caching.

In the article *Stream Processing of a Neural Classifier I* several terms and concepts related to GPGPU were introduced. A detailed description of the Fuzzy ART ANN implementation on a commodity graphics card, exploiting the GPU's parallelism and vector capabilities, was given. In this article, the aforementioned Fuzzy ART GPU-designed implementation is configured for robust real-time skin recognition. Both learning and testing processes are done on the GPU using chrominance components in TSL (*Tint, Saturation and Luminance*) color space. The Fuzzy ART ANN implementation recognizes skin tone pixels at a rate of 270 fps on an NVIDIA GF7800GTX GPU.

## BACKGROUND

Human body parts detection has important applications as a first step in many high-level computer vision tasks such as personal identification, video indexing systems and *Human-Machine Interfaces* (HMI). HMI needs real-time video processing while consuming as few system resources as possible. Skin color is widely used as a cue for detecting and tracking targets containing skin, such as faces and hands in an image. The final objective of skin color detection is to build a decision rule to segment skin and non-skin pixels in an image efficiently. The simplest solution defines skin colors as those that have a certain range of values in the coordinates of a color space. OpenVidia was one of the first computer-vision oriented developments able to run skin

tone segmentation on the GPU (Fung, 2005). For this purpose OpenVidia uses RGB (*Red, Green and Blue*) to HSV (*Hue, Saturation and Value*) color conversion and threshold filtering.

Statistical approaches for skin segmentation are based on the assumption that skin colors follow a certain distribution which can be estimated. These approaches normally make use of the chrominance components in a color space, thresholds and tunable parameters.

Neural Network approaches have been proposed to learn skin color distribution. Karlekar et al. used a MLP neural network to classify pixels into skin and non-skin colors (Karlekar & Desai, 1999). More complex models have been proposed to deal with changing conditions, such as varying illumination in the images. Sahbi et al. used an ANN for coarse level skin detection, and then the areas found were subjected to Gaussian color modeling with a fuzzy clustering approach (Sahbi & Boujemaa, 2000). Martínez-Zarzuela et al. used a GPU-based Fuzzy ART ANN implementation to learn skin colors in TSL (*Tint, Saturation and Luminance*) color space (Martínez-Zarzuela, Díaz, González, Díez & Antón, 2007). In their system, Fuzzy ART categorization process takes advantage of every fragment processor available in the GPU, so that several pixels can be tested simultaneously by the network, allowing recognition at high frame rates.

Some other researchers have made efforts for integrating different kinds of ANNs on the GPU for speeding up specific applications. Oh et al. developed a GPU-based MLP for text area classification in an image; achieving almost 20 times speed up over a CPU (Oh & Jung, 2004). Luo et al. implemented a MLP on the GPU for real-time ball recognizing and tracking in a soccer robot contest (Luo, Liu & Wu, 2005). Steinkraus et al. proposed using graphics cards for OCR and on-line handwritten recognition (Steinkraus, Simard & Buck, 2005). Finally, Bernhard et al. developed two image segmentation algorithms using spiking neural networks on the GPU (Bernhard & Keriven, 2006).

## STREAM PROCESSING FOR ANN-BASED SKIN RECOGNITION

### TSL Color Space

Color filtering is a powerful tool in computer vision applications including the detection and tracking of human

body parts. Color processing has low computational cost and is robust against geometrical transformations (e.g. rotation, scaling, transfer and shape changes). However, factors such as non-idealities in color cameras and illumination conditions can spoil the performance of filtering-based applications.

Color can be decomposed into three different components, one luminance and two chrominance components. Several researches have proved that skin colors have a certain invariance regarding chrominance components. Skin tone and lighting mainly affect the luminance value (Hsieh, Fan & Lin, 2005).

Different color spaces separating chrominance and luminance components have been used for skin color segmentation: YIQ, YCbCr, CIE-Lab, CIE-Luv, HSV, IHS and TSL (Phung, Bouzerdoum & Chai, 2005). In TSL color space (Terrillon, David & Akamatsu, 1998), a color is specified in terms of *Tint* (T), *Saturation* (S) and *Luminance* (L) values. TSL has been selected as the best color space to extract skin color from complex backgrounds (Duan-sheng & Zheng-kai, 2003) because it has the advantage of extracting a given color robustly while minimizing illumination influence. The equations to obtain the T, S and L components in normalized TSL space are:

$$T = \frac{1}{2\pi} \arctan\left(\frac{r'}{g'}\right) + \frac{1}{2}, \quad (1)$$

$$S = \sqrt{\frac{9}{5}(r'^2 + g'^2)}, \quad (2)$$

$$L = 0.299R - 0.587G + 0.114B, \quad (3)$$

where  $r' = (r - 1/3)$  and  $g' = (g - 1/3)$ , being  $r$  and  $g$  the chrominance components of the normalized rgb color model. The values of T, S and L are normalized in the range [0,1]. For  $R = G = B$  (achromatic colors),  $T = 5/8$  and  $S = 0$  are taken.

### Fuzzy ART Off-Line Training on the GPU for Skin Recognition

*Adaptive Resonance Theory* (ART) systems are comprised of three layers or fields of nodes. Fuzzy ART is an extension of the original ART 1 system that incorporates computations from *fuzzy set theory* into the ART network, and thus making it possible to learn

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