Brain Emulation for Image Processing

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Abstract

We present an innovative and high performance embedded system for real-time image filtering based on the operating principles of the human brain pattern matching procedure. This system is based on the evolution of hardware and algorithms developed for High Energy Physics (HEP) and more specifically for the execution of extremely fast pattern matching for tracking of particles produced by proton-proton collisions in hadron collider experiments, such as the ATLAS FTK [1]. A miniaturized version of this complex system is being developed for pattern matching in generic image processing applications. The design uses the flexibility of Field Programmable Gate Arrays (FPGAs) and the powerful Associative Memory Chip (ASIC) to achieve real-time performance. The system works as a contour identifier able to extract the salient features of an image. It is based on the principles of cognitive image processing, which means that it executes fast pattern matching and data reduction mimicking the operation of the human brain.

Algorithm Description

Static Images

Black/White ..... 2^9=512 patterns: 101-010-100, ... , 111-011-001

4 lv of Gray ..... 2^18=256 Kpatterns: 00,00,01-00,01,00-11,00,10 ....

Movies 2^27=128 Mpatterns: 111,000,000 - 000,111,000 - 000,000,000

Algorithm Sequence [2]:

1° Stage → Training: calculate the frequency and entropy of each pattern in the sample images/frames to select the relevant patterns to be used as reference for the matching process.

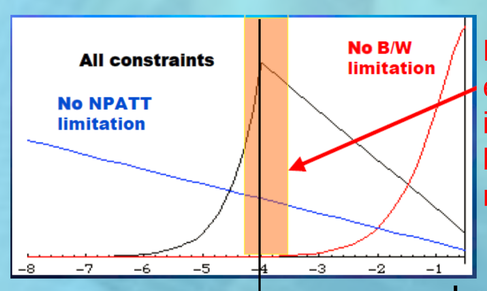
2° Stage → Run: send the image patterns to AM chip to be filtered matching the relevant patterns.

The AM chip is a CAM like ASIC that executes pattern matching in parallel [3].

Pattern Selection Definition

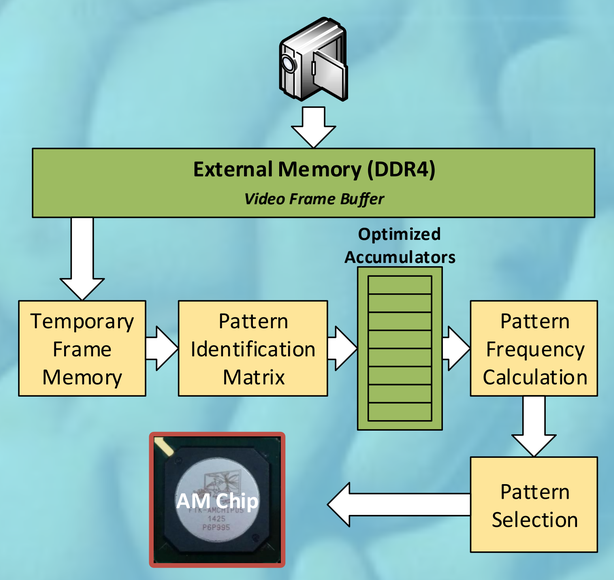
p_i : probability pattern "i" in sample image set
N_{tot} : total number of patterns
N : number of stored patterns (available memory space)
W : available bandwidth
H : measure of output information

$$H = \sum_i -p_i \log(p_i) \quad \text{(Boltzmann entropy)}$$

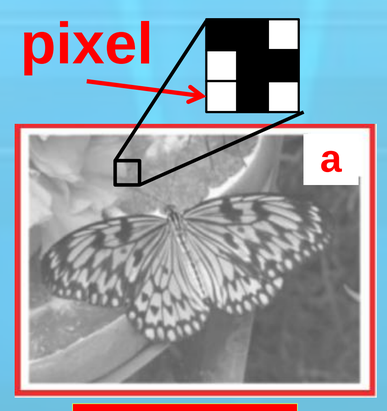


Patterns that are efficient carriers of information given the bandwidth (W) & memory limits (N) [2]

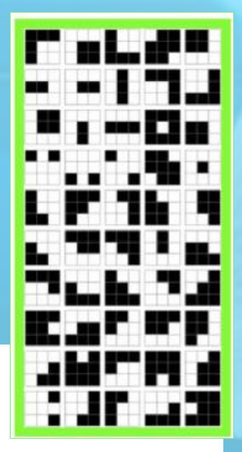
Training Phase Implementation

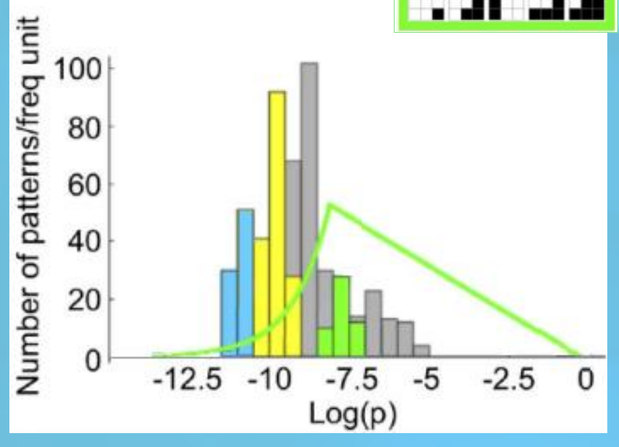


Pattern Selection and Impact on Output



Info: 100%



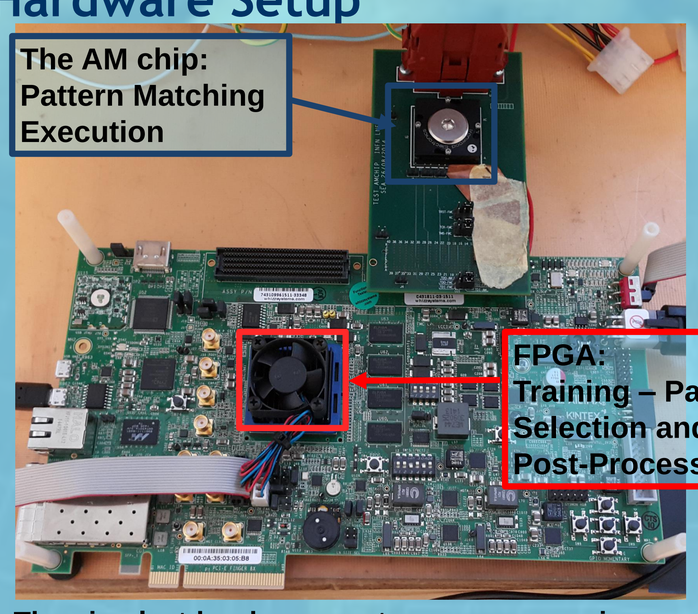


50 relevant patterns

16 relevant patterns

An example of pattern selection (as described in [2]) performed on a natural digitized image representing a butterfly. It can be seen that the filtered images (b) and (c) obtained with the selection of "relevant patterns" are recognizable, while in image (d) filtered with low probability patterns, the important features are lost.

Hardware Setup



The simplest hardware system we can use is a combination of a Xilinx Kintex Utrascale evaluation board (KCU105) with a small mezzanine card housing the Associative Memory chip AM05, both designed by M. Beretta, F. Crescioli, A. Stabile et. al [3].

The training and post-processing step (e.g. Clustering as a post-processing algorithm in [4]) of the algorithm are implemented on the FPGA to take advantage of the device flexibility. The Associative Memory chip can be used to execute very fast pattern matching.

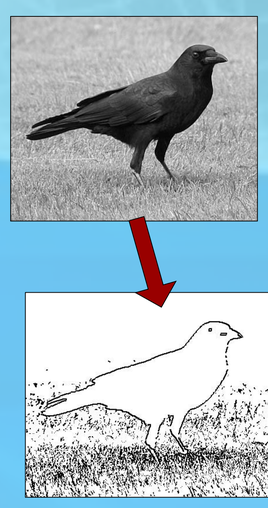
Simulation and Implementation Results

The Training System is implemented and tested on the Kintex Ultrascale FPGA. We use a set of sample images to test and verify the system operation.

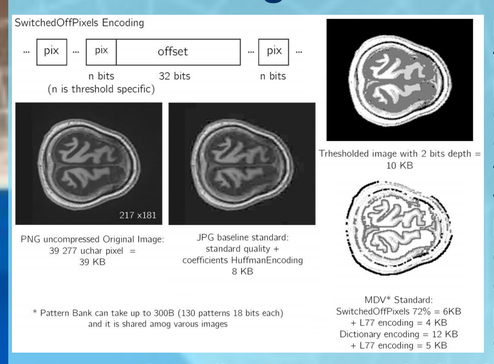
The complete training implementation requires less than 2% of the FPGA LUTs and 2.4% of the available BRAMs for processing of black and white images.

We use a 250 MHz clock. To process a 512x512 pixel image less than 2,5 msecs are required.

The software simulation instead requires more than 3 secs to execute the training algorithm for the same image on a 3rd generation i5 processor with 4 GB RAM. The results for 50 relative patterns are comparative in quality with a Canny Edge Detector.



Medical Image Processing using Brain Emulation



Decision-making image processing pipelines have demonstrated their ability in predicting the possible conversion from the pathological status of Mild Cognitive Impairment (MCI) to Alzheimer's disease (AD) [5]. The algorithm proposed in [5] is based on the classification with Support Vector Machine (SVM) classifiers of brain features extracted at the voxel level on the gray matter segmented from the original structural MRI of 635 subjects, including AD and MCI patients, and age-matched controls. The application of an edge-enhancement filter before the segmented grey matter voxels are classified by an SVM can possibility enhance key features for the prediction of the AD conversion. A dedicated filtering strategy based on [2] has been set up and initially tested o 2D images.

An example a slice 217 x 181 pixels of an MRI image in Nifti format was compressed used the presented model. The images were obtained by sampling a small set of 8 MRI's 2D slices of patients in different conditions. In this case features sampled were 2D patches 3x3 pixels 2 bit depth. Greyscale levels were selected in proximity of probable WM (White matter), GM(Grey Matter) and CSF (Cerebrospinal Fluid). As expected from an edge enhancement filter, the border between grey and white matter are definitely highlighted.

Future Targets

- **Extend the implementation to be operational for 4 levels of gray and 3D images/movies**
- **Create a small mezzanine card (FPGA+Amchip) to be used as a hardware accelerator for normal CPUs**
- **Targeting biomedical, security, space applications**

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References

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Acknowledgements

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