SUMMER SCHOOL “SUMMER STUDENTS AT FERMILAB AND OTHER US LABORATORIES
PISA 25/07/2017

PATTERN MATCHING: FROM HIGH ENERGY PHYSICS TO IMAGE PROCESSING

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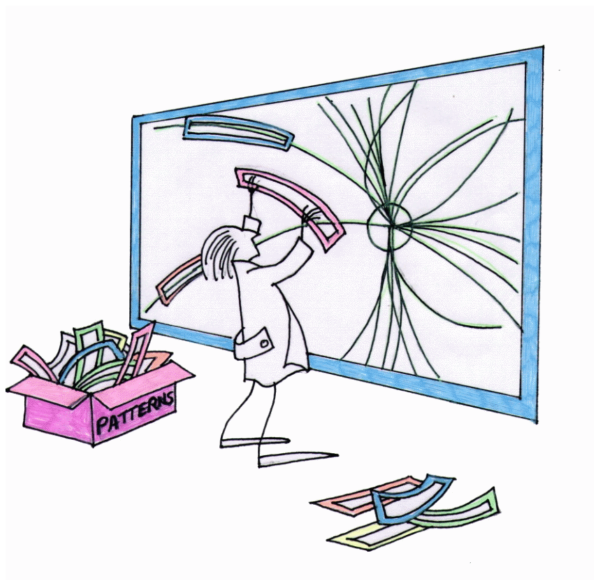

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Advanced Image Processing Implementations: A Multidisciplinary Approach

- Advances in sensors, communications, computation speed, size of storage (data centers) etc.
- Data increasing in quantity and diversity
- **What is needed:**
  Fast and efficient ways to process the data → data traffic reduction with minimal information loss

Advanced Image Processing Implementations: A Multidisciplinary Approach

- Image Processing: Increasing resolutions and frame rates

- Applications
  - High Energy Physics
  - Biomedical: CAT scans, MRI, several forms of diagnostic equipment
  - Security applications (satellite imaging)
  - Cognitive imaging: image processing that emulates the way the brain identifies “meaningful” patterns

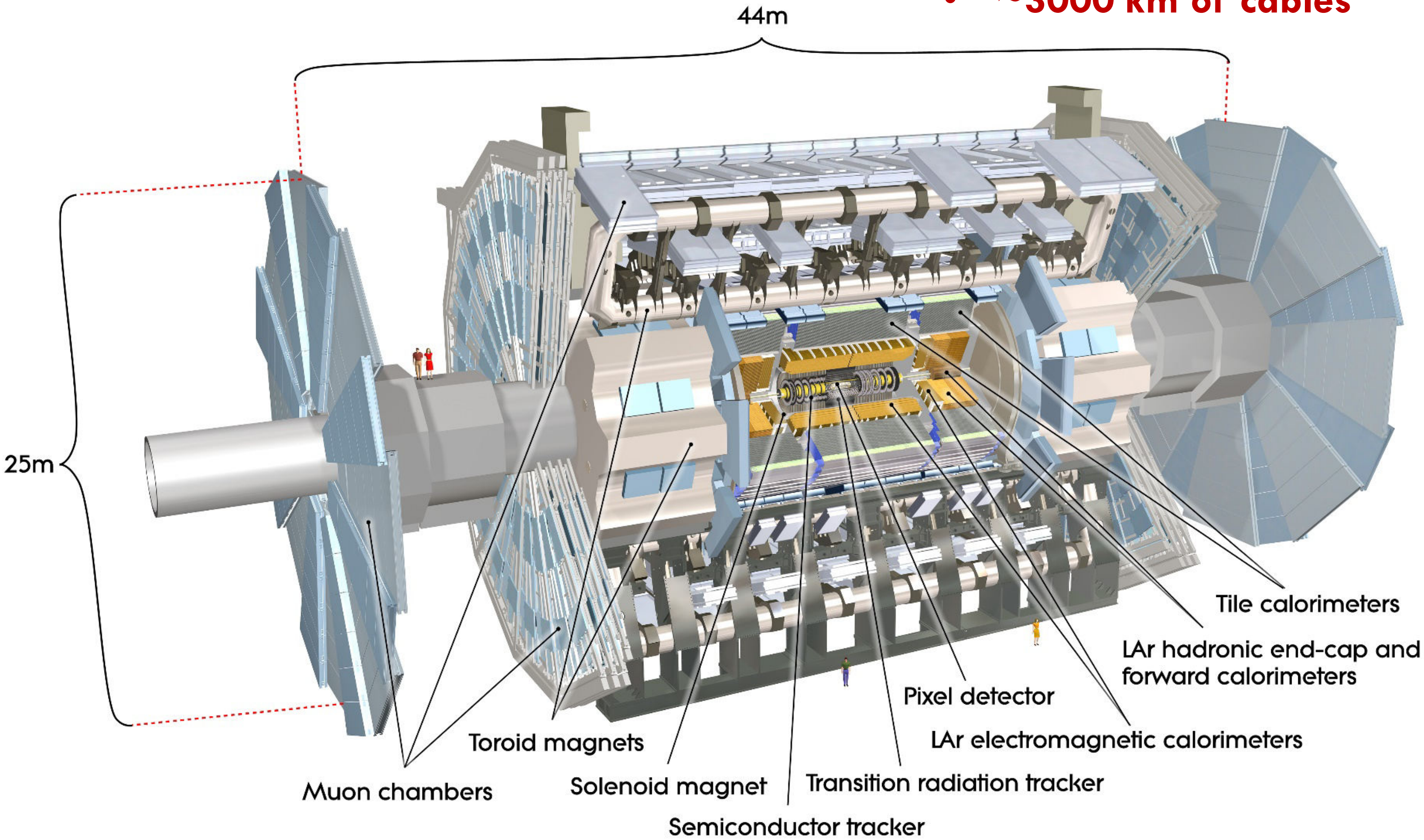
High Energy Physics and Image Processing

- **High Energy Physics has a well known problem – how to accurately process massive quantities of data in real time**

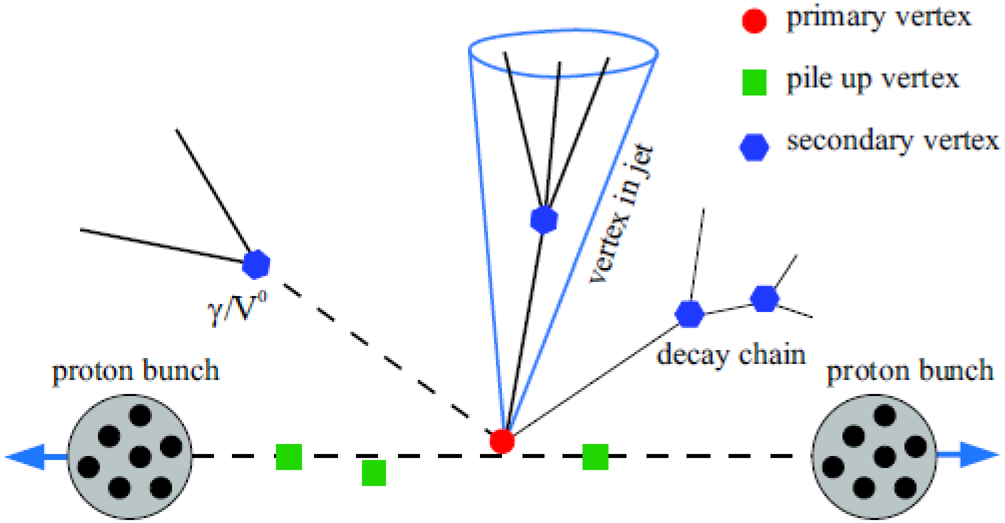
- **The universe is governed by probabilistic physics**
  - **One measurement tells us very little**
  - **However carefully we set up an experiment, probabilistic physics decides what we observe**
  - **If we want to observe something rare, we may have to find a few occurrences (events) hidden in vast numbers of other events**

The ATLAS Detector

- **Overall weight 7000 tones**
- **~100 million electronic channels**
- **~3000 km of cables**



The ATLAS Detector



- **ATLAS "sees" bunches of collisions (tens of superimposed events) every 25ns**
- **That is 40 million/second or about 15 trillion bunch collisions per year**

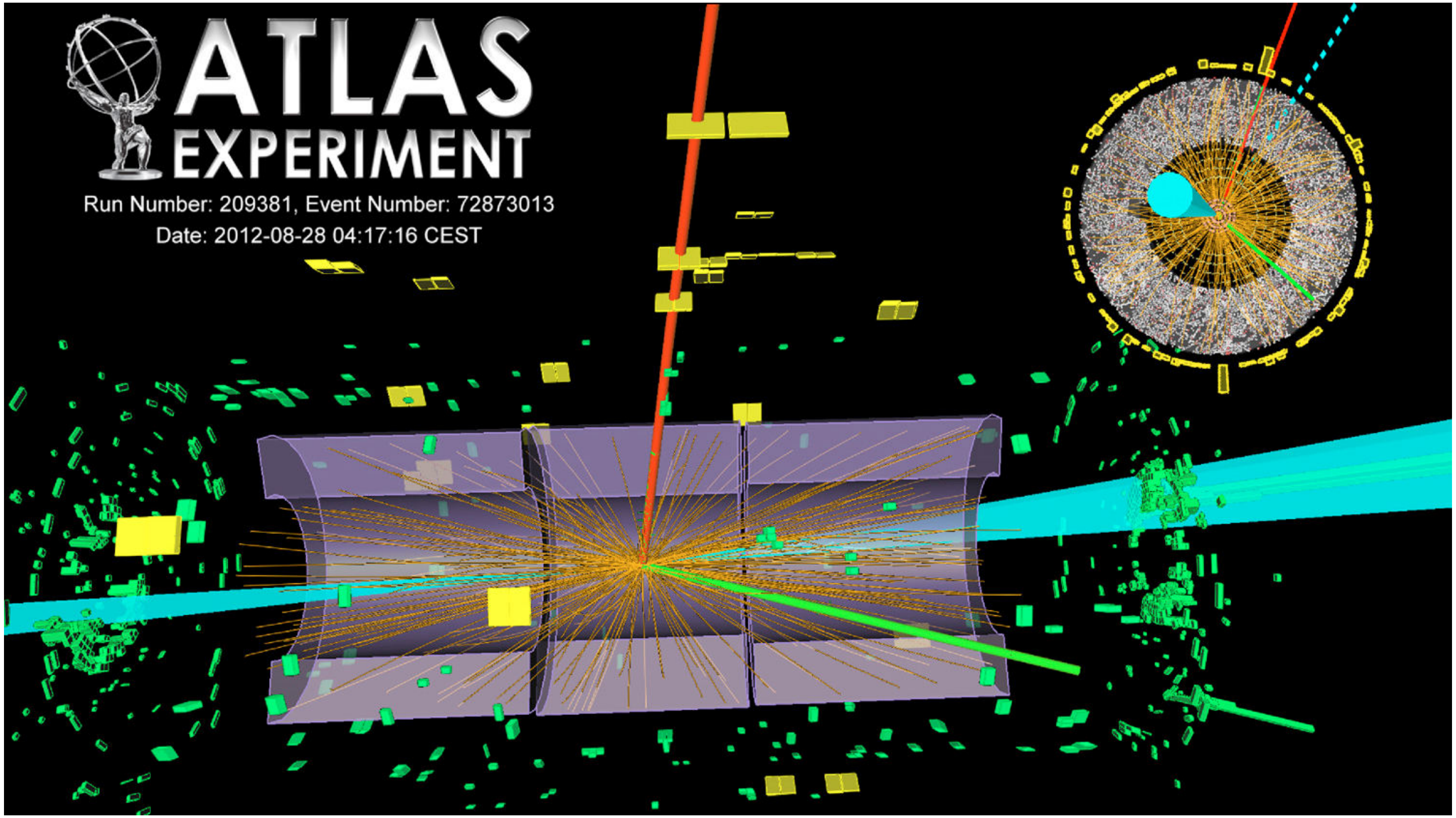
High Energy Physics and Image Processing

- Raw analog data rate from Large Hadron Collider (LHC) detectors (event rate **40MHz**)
  - About **one Petabyte per second**
  - This would cost about **1 trillion euros** for storage

- In real time, we throw away the data not needed to make discoveries → affordable storage
  - We really do **throw away 99.9999% of LHC data** before writing it to persistent storage
  - **But the discoveries with the greatest impact are those we don't expect**

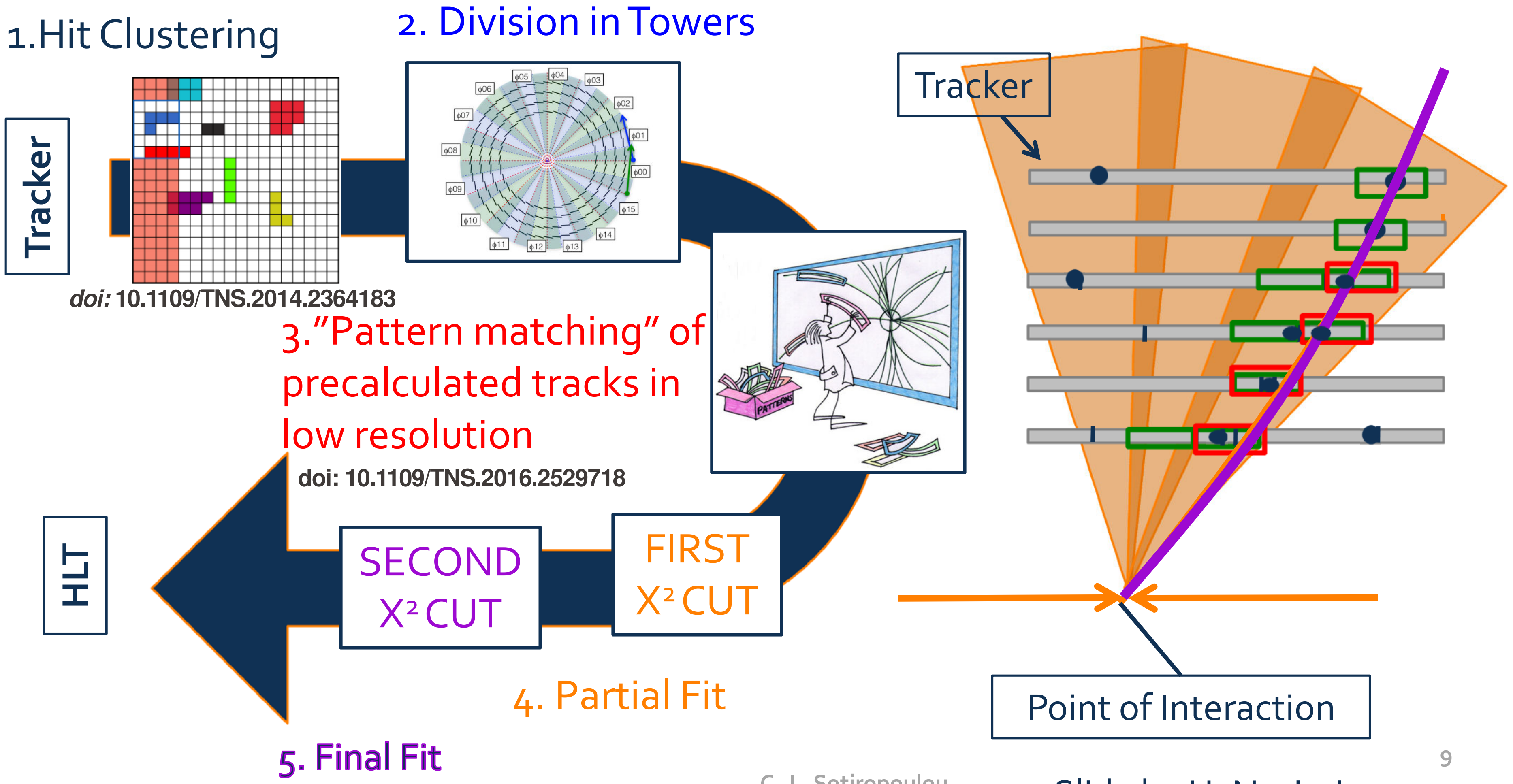
"Big Data Needs High Energy Physics especially the LHC", presentation by R. P. Mount

Advanced Image Processing In High Energy Physics



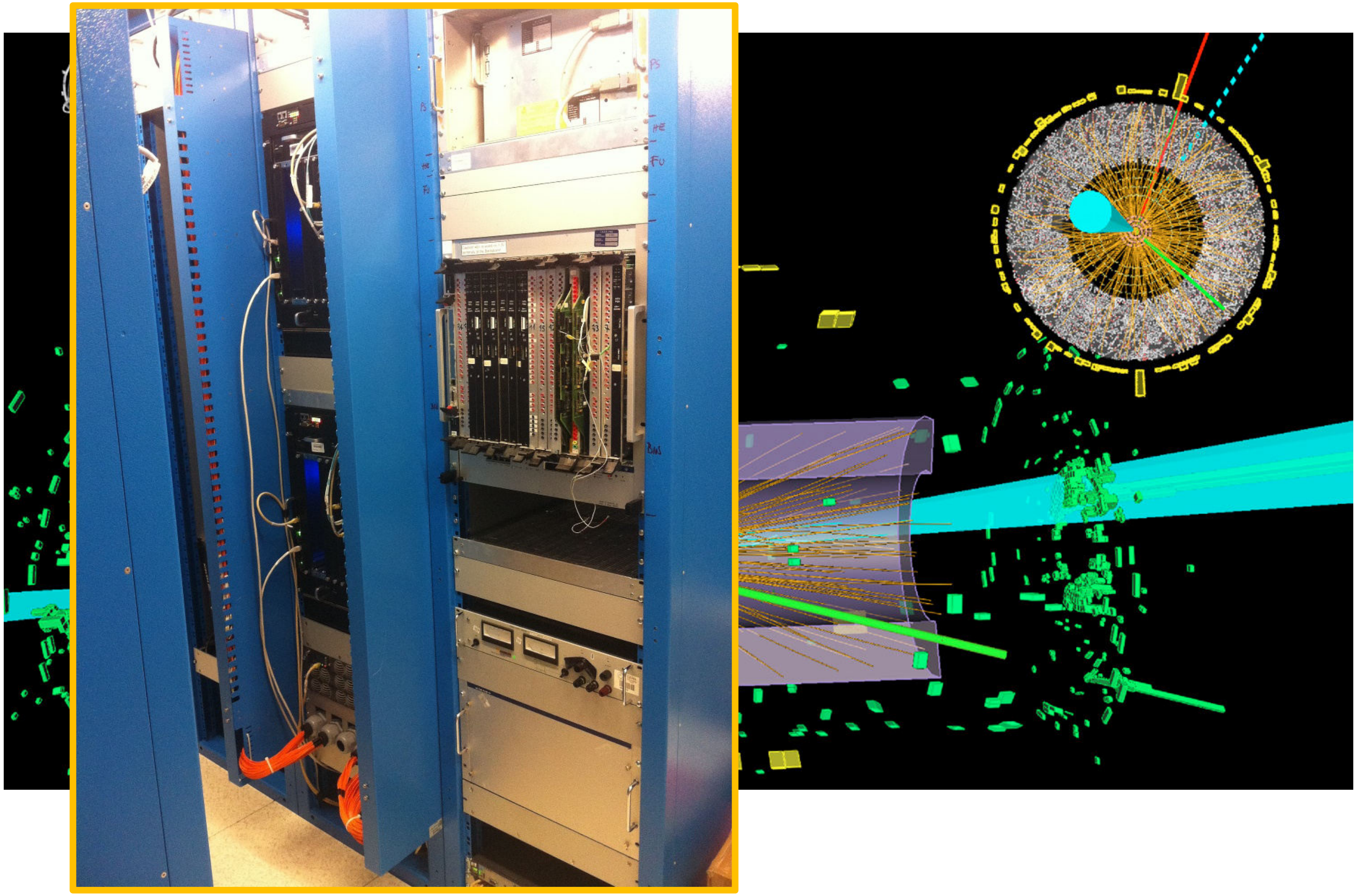
The Fast TracKer System

Full scan real-time tracking system: recontstructs all the tracks that belong in one event with a latency of ~100 μs -> Problem devided in **5 stages**:

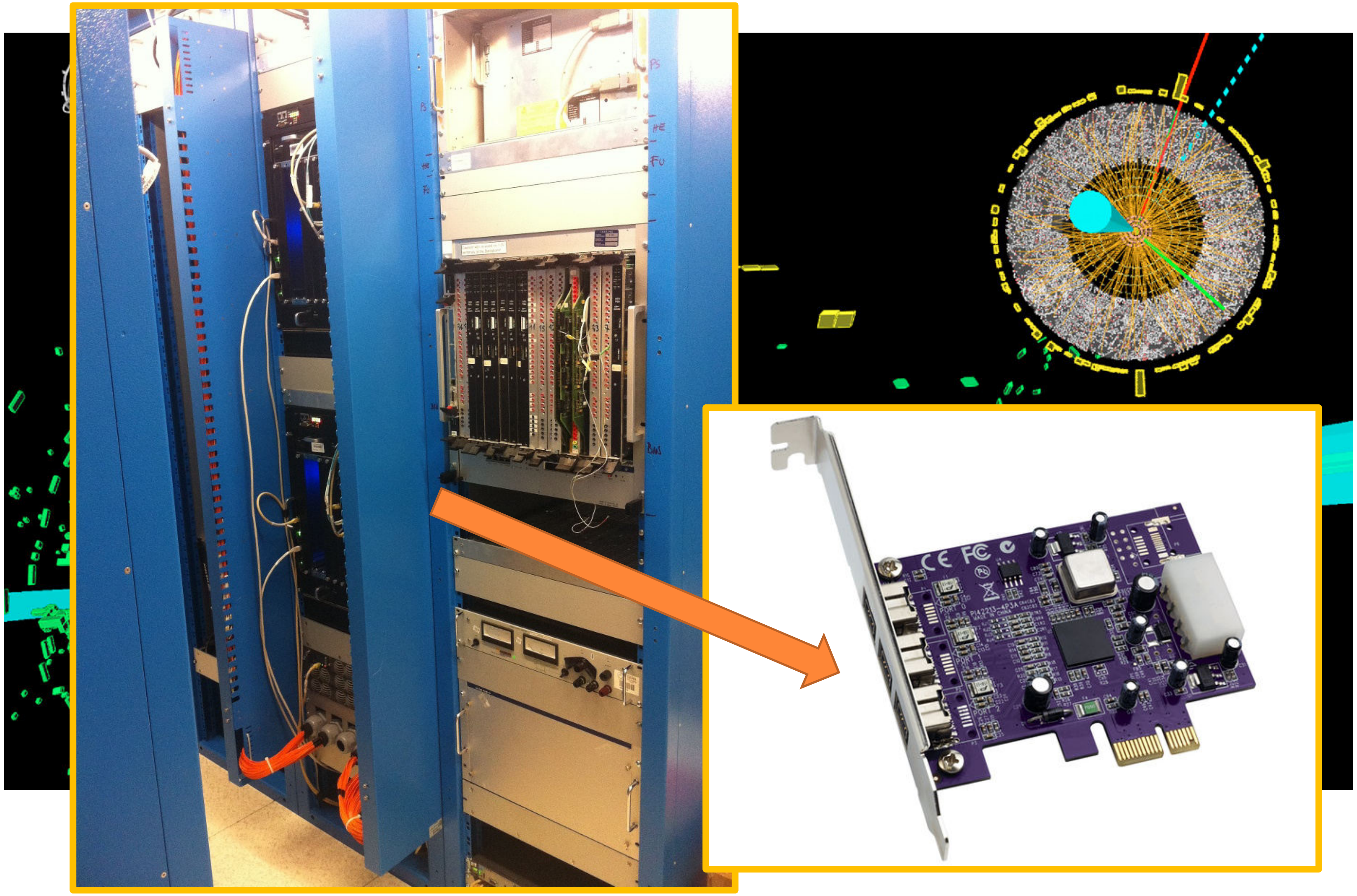


Slide by H. Nasimi

Advanced Image Processing In High Energy Physics



Advanced Image Processing In High Energy Physics



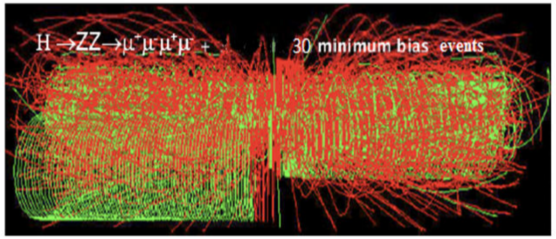
The Idea → Multidisciplinarity

- **There is a concept that has been proven to work (algorithm and hardware) → Fast TracKer (FTK)**

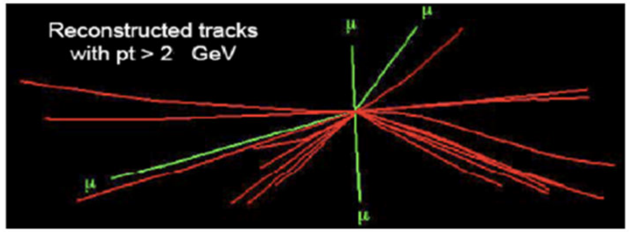
- **Looking for alternative scientific and industrial fields to apply what already exists and develop it further → Medical Image Processing**

A New Approach to Image Processing

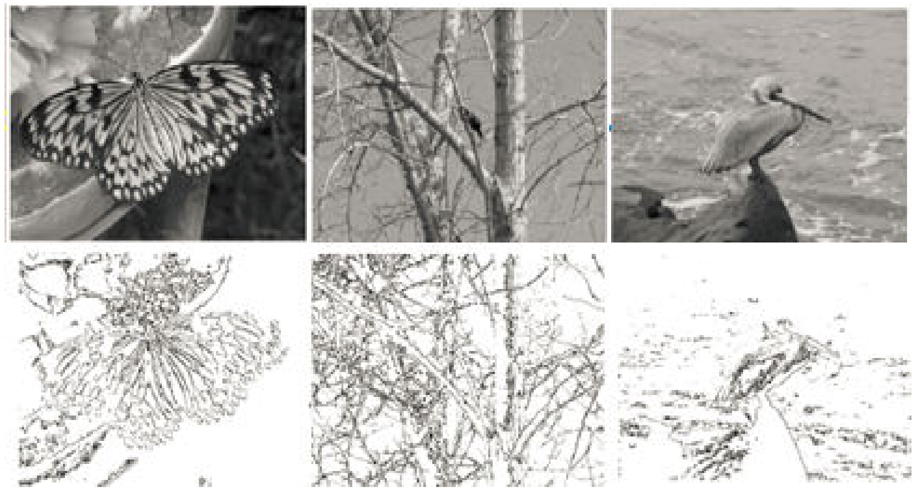
- The FTK Processor is a very fast, powerful and efficient pattern matching machine
- **The particle tracking problem is in fact an image processing problem**



HEP



Before Filtering



After Filtering

Brain Emulation

- When a human is in a situation of stress (danger etc.) his/her brain does not look for the details in the visual stimulus

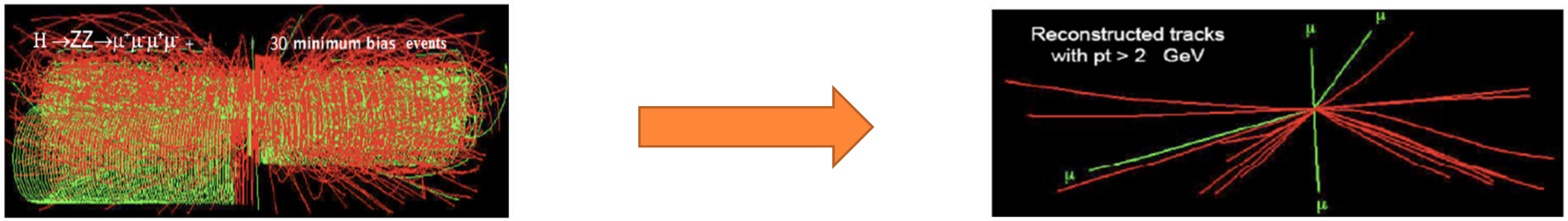
Brain Emulation

- The only single objective is to identify the source of the danger (identify the form)

[1]*M. Del Viva, G. Punzi, and D. Benedetti. Information and Perception of Meaningful Patterns. PloSone 8.7 (2013): e69154.*

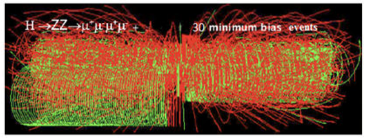
Brain Emulation

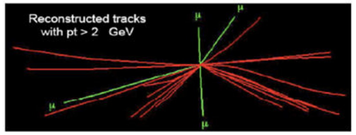
- Studies conducted have demonstrated that the brain uses a "pattern matching" process very similar to the one used by the trigger systems of HEP experiments

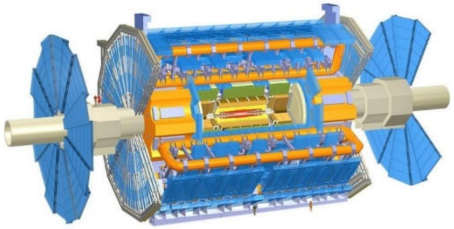


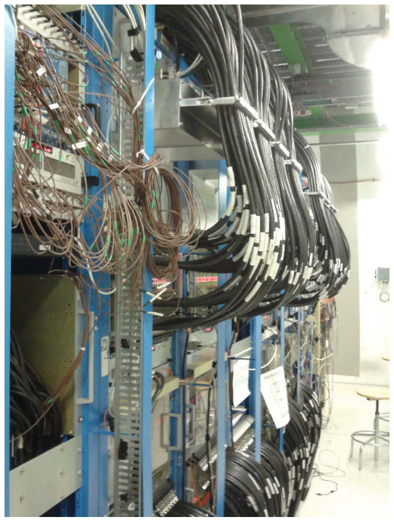
Brain Emulation

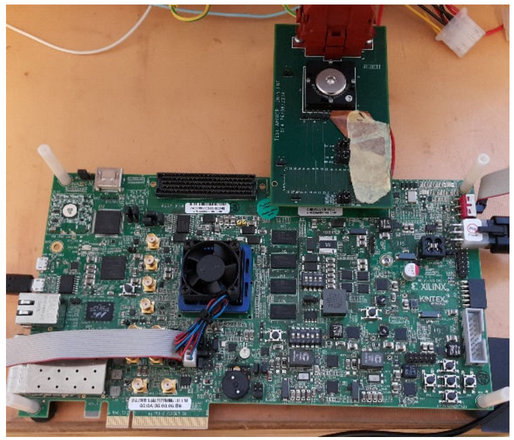
- We can use hardware developed for HEP adjusted in a "mini version" for Image Processing applications











Brain Emulation

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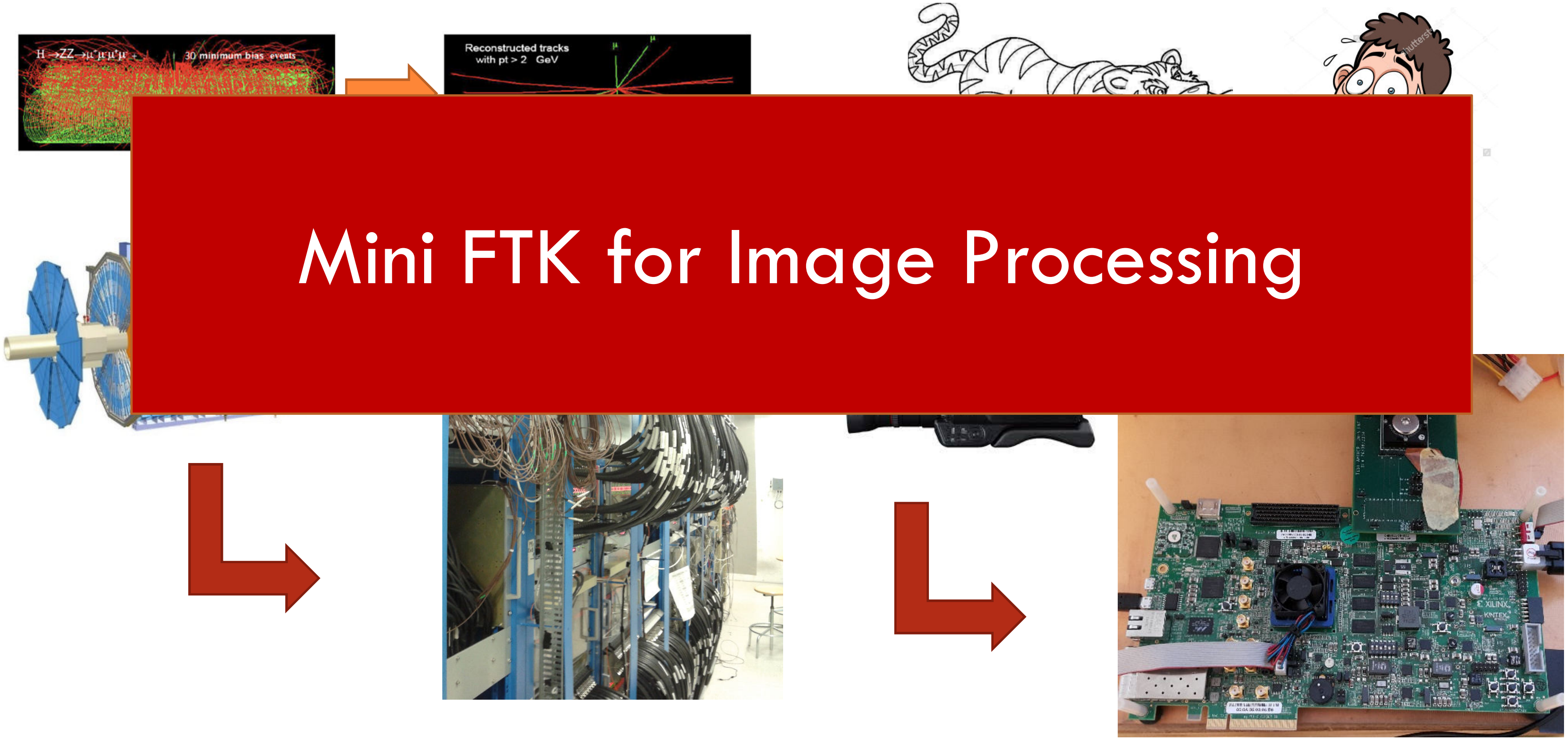


Mini FTK for Image Processing

FTK for Image Filtering

- Major difference between HEP and Human Brain:
  - For HEP we are aware a-priori of the relevant patterns
  - The Human Brain is trained in real time
    (we are not aware of the patterns beforehand and we always adjust to new environments)

- **Target:**
  Design and prototype a pattern matching machine that executes both training and filtering in real time using high performance embedded systems (FPGAs, ASICs and combination of the two - SiP / System In Package)

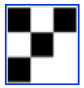
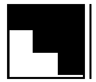
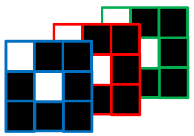
Cognitive Image Processing Algorithm

- Two phase algorithm and implementation
  - **Training Phase (Pattern Selection - Training):**
    Select an image or video sample and use it to identify the relevant patterns for a specific application with specific parameters.
    Training should be executed in real time in case the environment or application parameters change.

  - **Pattern Matching (Real Time Execution):**
    Real time pattern matching with the preselected patterns from the training phase.

Cognitive Image Processing: Training Phase

- **Build small arrays of pixels (3x3 for static images or 3x3x3 for movies – 3rd dimension for time) that are AM patterns** *(M. Del. Viva, G. Punzi)*

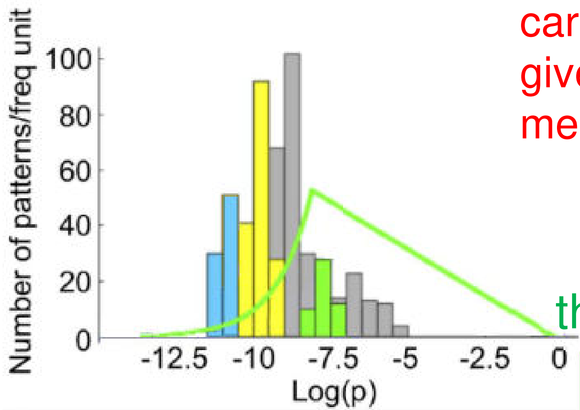
- B/W   2^9=512 patterns: 101-010-100, ……. , 111-011-001
- 4 gray level   2^{18}= 256 Kpatterns: 00,00,01-00,01,00-11,00,10 …..
- B/W + time  2^{27}= 128 Mpatterns: 111,000,000 - 000,111,000 - 000,000,000

- **Training:** Calculate the frequency of **each pattern** in the sample images/frames

- Compute **Probability Density Histograms** (**PDHs**)

Cognitive Image Processing: Pattern Selection Impact

- **Choice of relative patterns:** Choose the pattern set that **maximizes entropy H under real constraints**



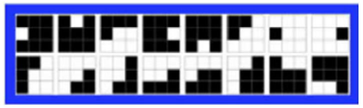
Patterns that are efficient carriers of information given the bandwidth (W) & memory limits (N)

$$H = \sum_{i}^{NPatt} [-p_i Log_2(p_i)]$$

$$f(p) = \frac{-p\log(p)}{\max(1/N, p/W)}$$

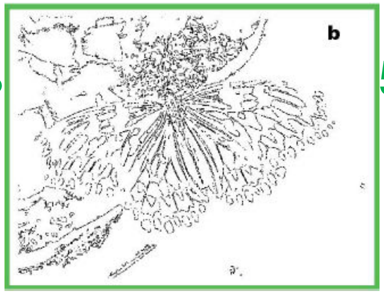
Accepting only these 50 patterns

Accepting only these 16 patterns

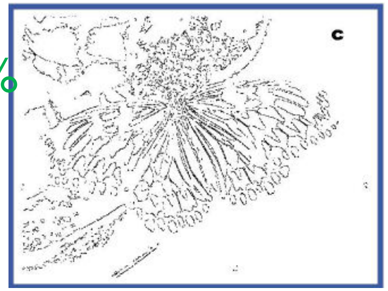


4 levels of grey: 2^{18} patterns Stored N=2000

9.8%



5.5%



Simulation Demonstrator

Medical Image Processing

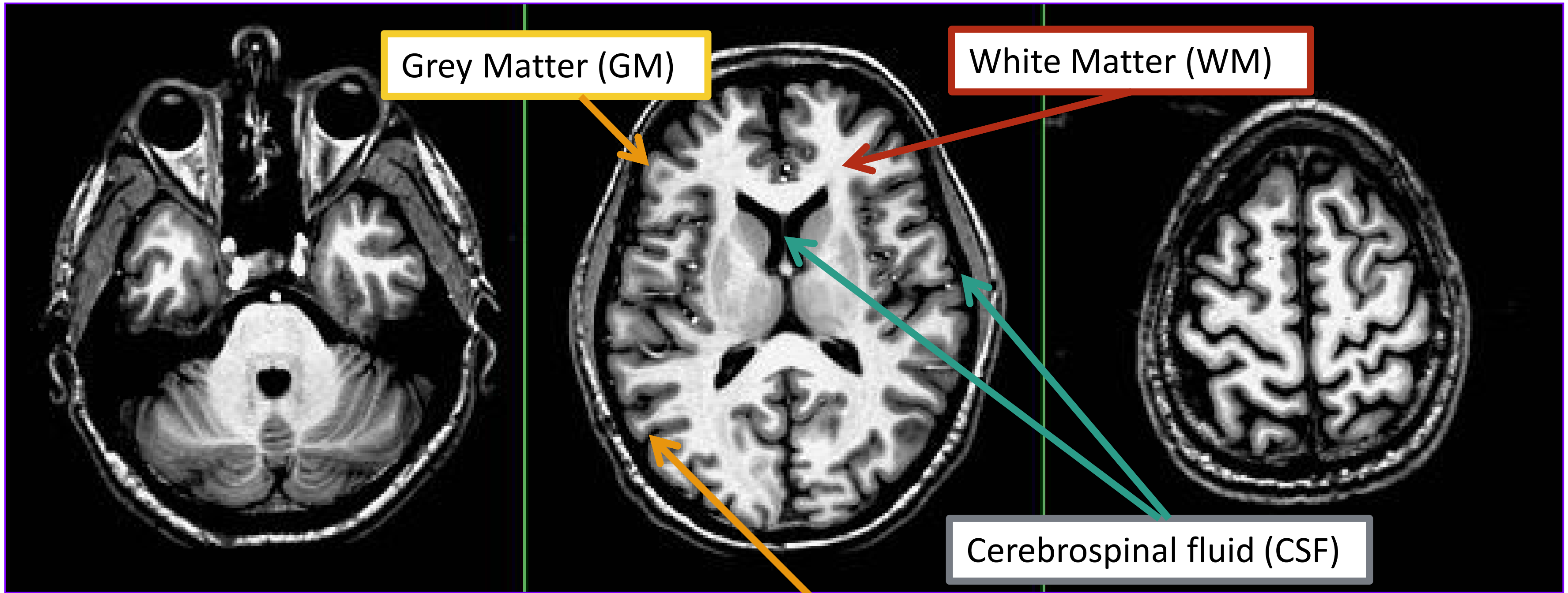
- The brain emulation algorithm works very well as a **contour identification system** (edge detection)

- We are exploring the use of this filter in **Magnetic Resonance Imaging (MRI)** for the identification of diseases such as the progression of Mild Cognitive Impairment (MCI) to **Alzheimer's Disease (AD)**

- In collaboration with the ARIANNA project (INFN)

T_1-weighted brain images

Axial slices of a human head with spatial resolution of 1 mm^3



Grey Matter (GM) cortex can by followed and cortical thickness can be evaluated to investigate GM involvement in pathological conditions.

A. Retico

Medical Image Processing

- We contacted preliminary studies for the feasibility of the task by using our simulation framework on 2D MRI brain images

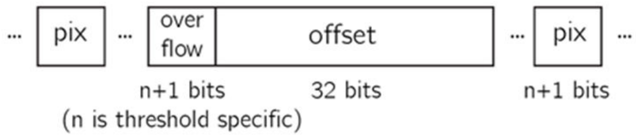
- A) Input Image B) Thresholded Image C) Filtered Image

- We could successfully identify the different regions of the brain

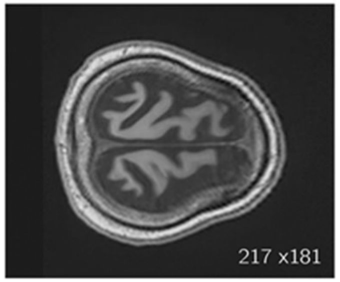
Medical Image Processing

Compression Evaluation

SwitchedOffPixels Encoding



Trhesholded image with 2 bits depth =
10 KB



PNG uncompressed Original Image:
39 277 uchar pixel =
39 KB

JPG baseline standard:
standard quality +
coefficients HuffmanEncoding
8 KB

MDV* Standard:
SwitchedOffPixels 72% = 8KB
+ L77 encoding = 5.5 KB
Dictionary encoding = 12 KB
+ L77 encoding = 5 KB

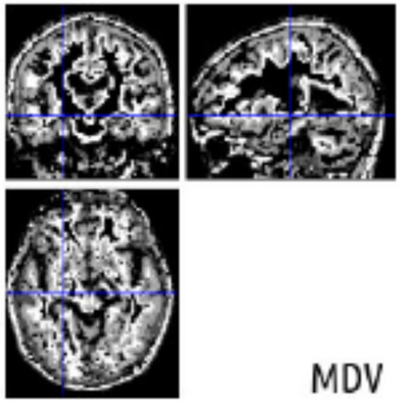
* Pattern Bank can take up to 300B (130 patterns 18 bits each)
and it is shared amog varous images

Compression is data dependent

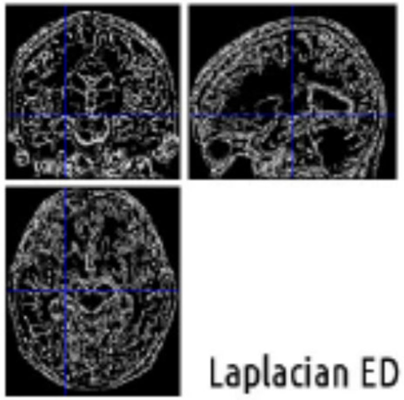
Medical Image Processing

- 3D edge detection studies

original

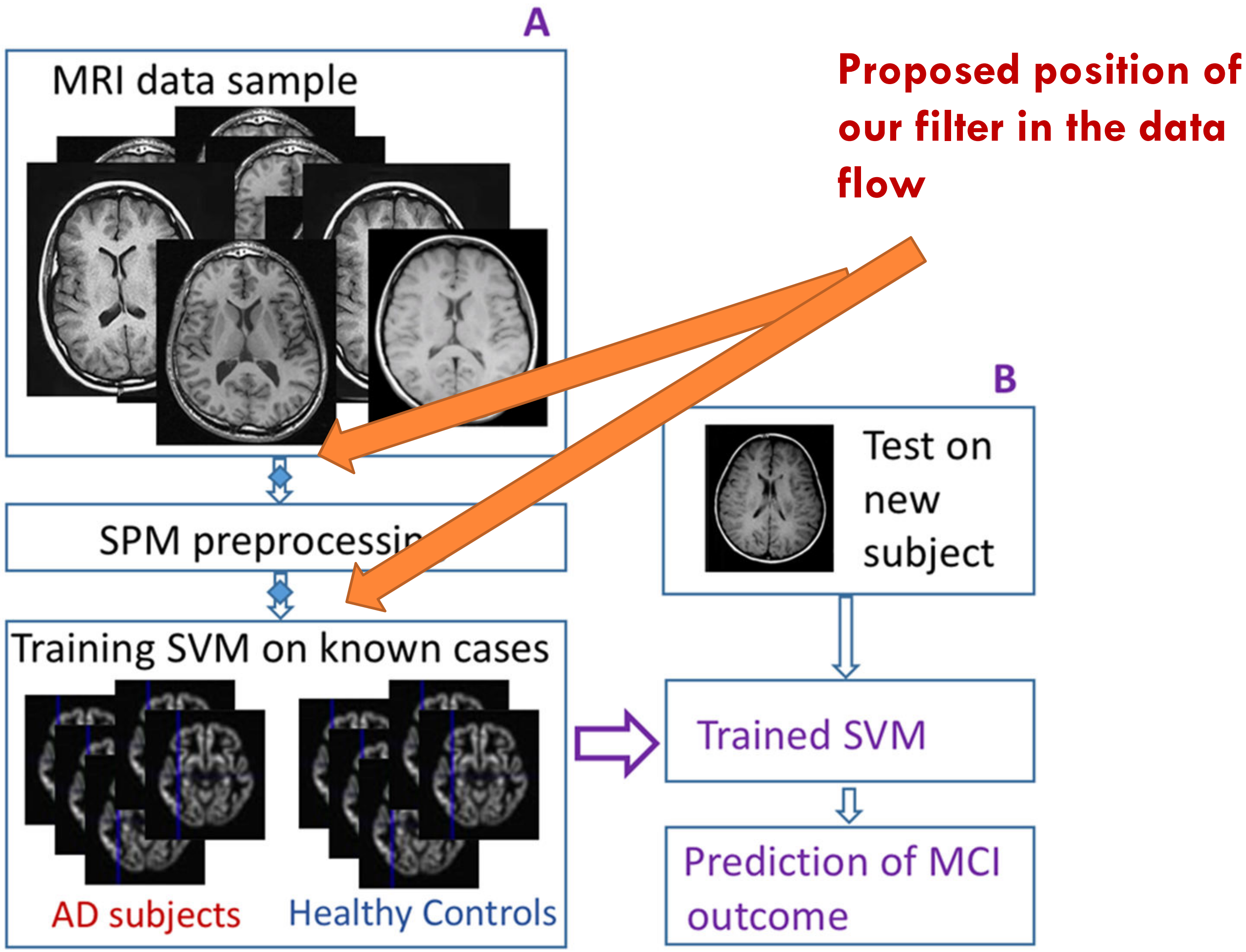


MDV



Laplacian ED

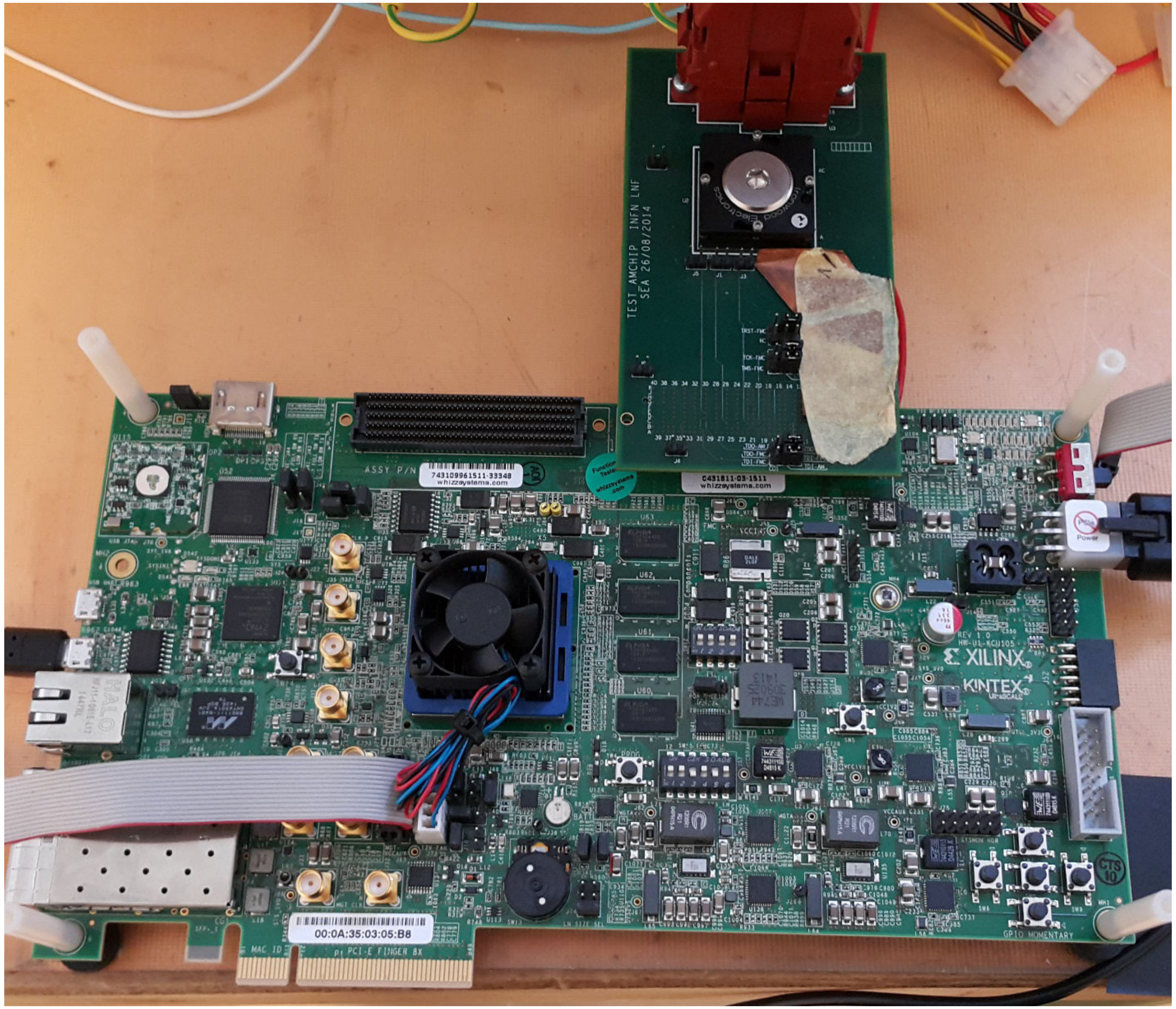
Medical Image Processing



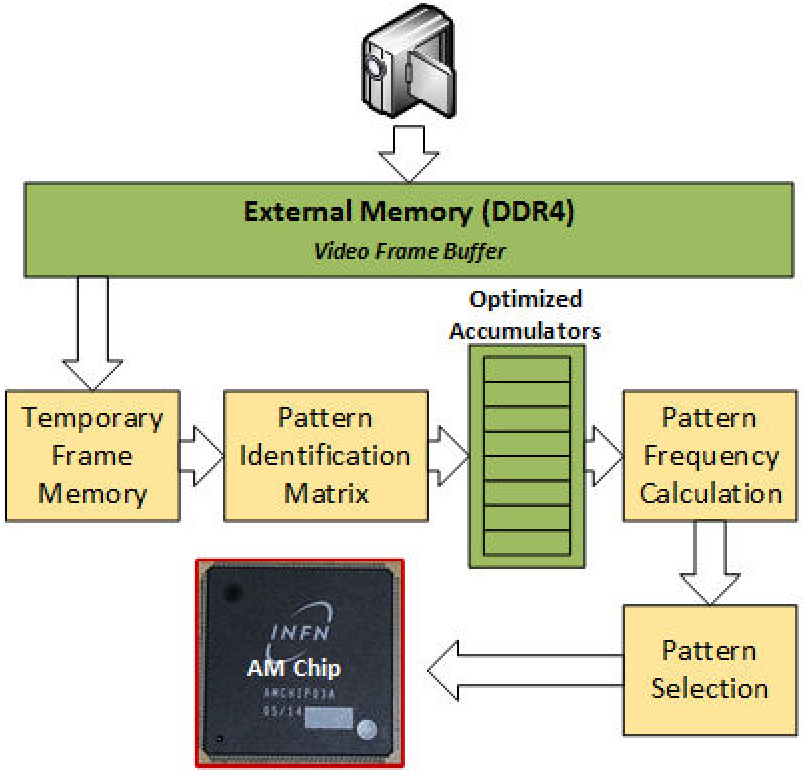
Hardware Implementation

- A platform based on FTK hardware is used:
  - Combination of powerful FPGAs (Kintex Ultrascale KCU105) with ASICs (the Associative Memory chip – AM)
- The filtering is implemented in two phases just like the algorithm
  - The Training Phase
  - The Pattern Matching Phase
- Most of the functions are executed by the FPGA with the only exception being the data taking that is executed by the AM under the FPGA control

Hardware Platform



Training Phase Implementation



Implementation Results - Training

- The training phase has been implemented on a Xilinx Kintex Ultrascale XCU040 of the KCU105
- The training phase implementation is generic and the resource requirements change from 2-D to 3-D implementation
- 2D B/W Images implementation results:
  - The implementation requires less than 3% of the FPGA LUTs and 2.5 % of the available BRAMs.
  - The clock used in the implementation is 250 MHz.
  - To process a sample of 1000 images of 217 x 181 pixel resolution the training hardware requires 116 ms.
  - A i7 skylake processor with 8 Gb RAM requires instead more than 32 secs to execute the training algorithm for an image sample of the same size (single thread execution).

Implementation Results – Pattern Matching

- The data acquisition phase has been implemented on a Xilinx Virtex V6-240T of the HTG-V6 evaluation board. (Intermediate Step)
- The complete data acquisition phase implementation requires 1% of Slice Registers, 1.3% of Slice LUTs, 9 FIFO@36bits logic and 50% of the FPGA device GTX resources.
- The clock used in this implementation is 100 MHz.

Event Processing Time (AMBoard Estimation)

- We have estimated the processing latency for the data taking exploiting the AM infrastructure of the FTK system

- The processing time is ~15,3 ms to filter one 217x181 B/W image (pattern size: 9 bits). The same image when processed by a i7 skylake processor with 8 Gb of RAM requires 170 ms.

Future Plans

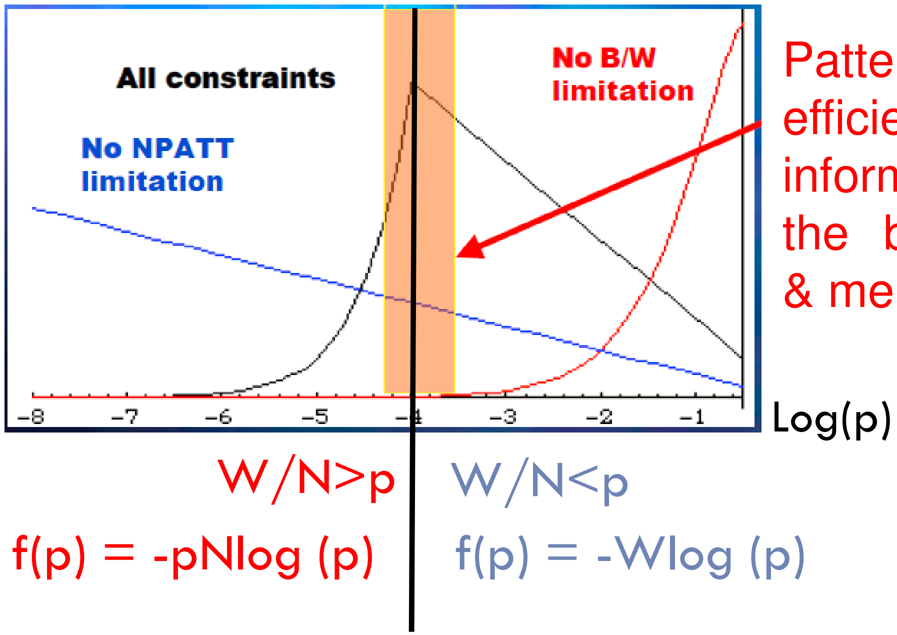
- More resources available on the FPGA device → New technology, new design approaches, greater challenges (Ultrascale)
- Merge the devices on a single chip (SiP)
- Targeting the development of a portable and flexible hardware accelerator (possibly with a PCI type interface) to be easily interconnected with a PC

- Thank you!

Cognitive Image Processing: Training Phase

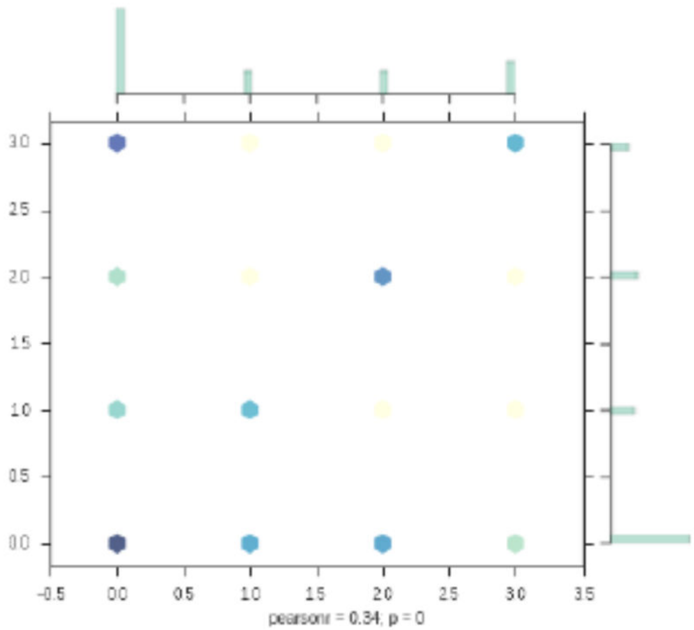
- **p_i** : probability pattern "i" in sample image set
- **N_{tot}** : total number of patterns
- **N** : number of stored patterns (available memory space)
- **W** : available bandwidth
- **H** : measure of output information

- **$H = \sum_i -p_i \log(p_i)$ (Boltzmann entropy)**

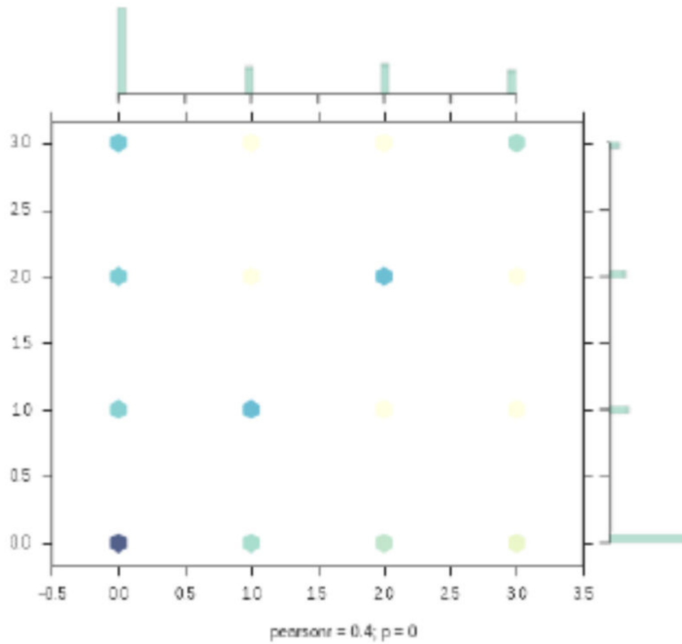


Patterns that are efficient carriers of information given the bandwidth (W) & memory limits (N)

Medical Image Processing



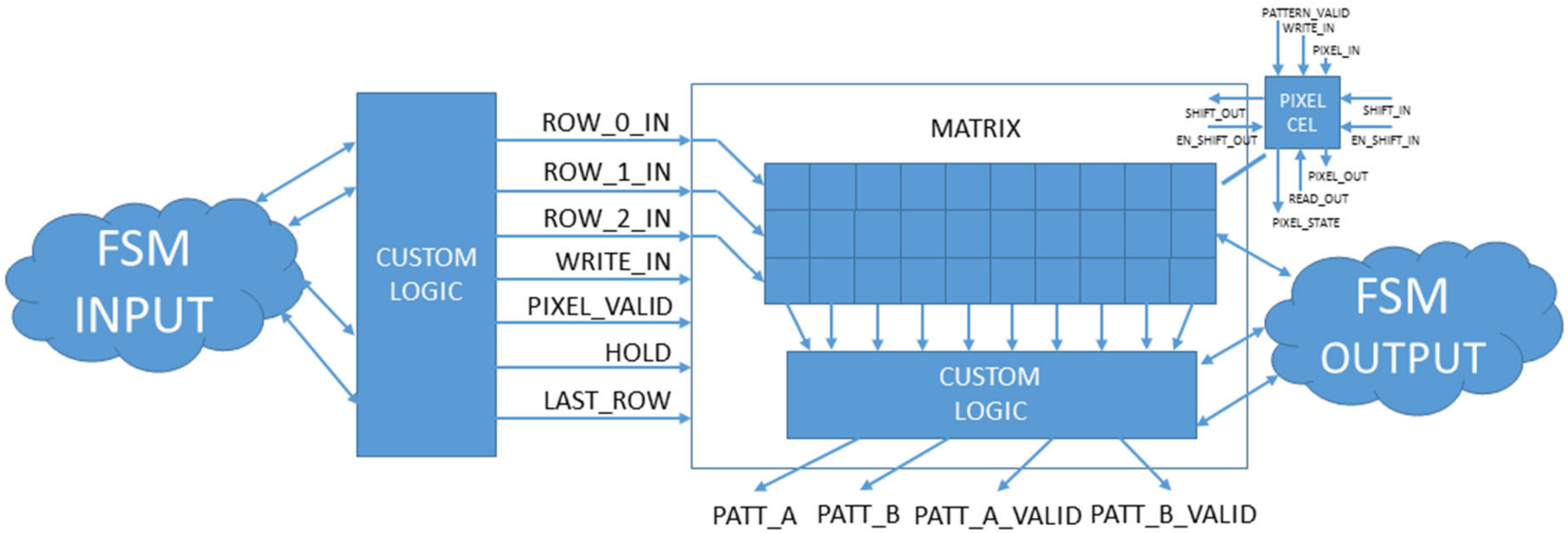
(a) patient: AD-1



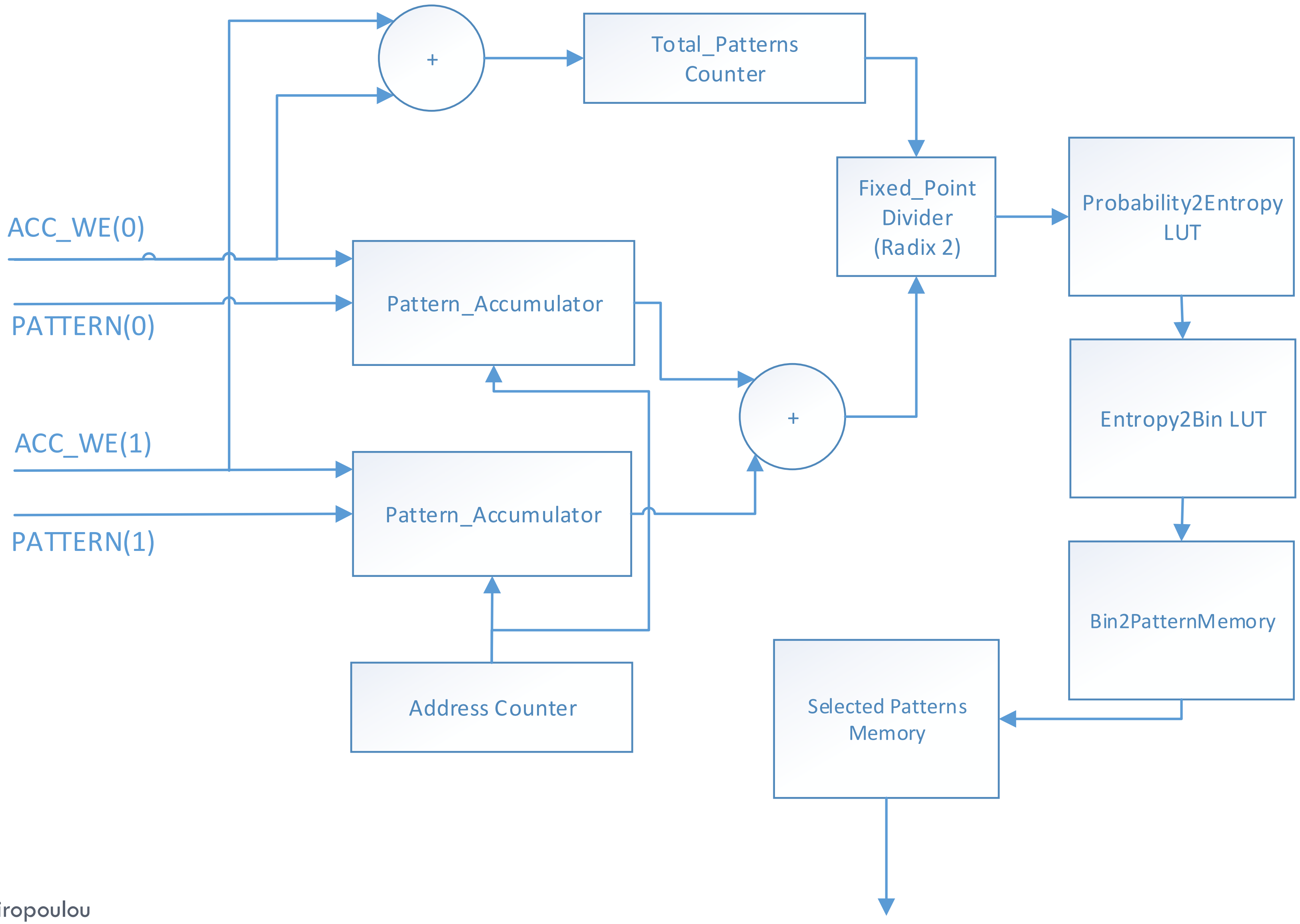
(b) patient: AD-7

Pearson correlation 0.38 (value over 0.3 is a positive value)

Matrix Identification Module



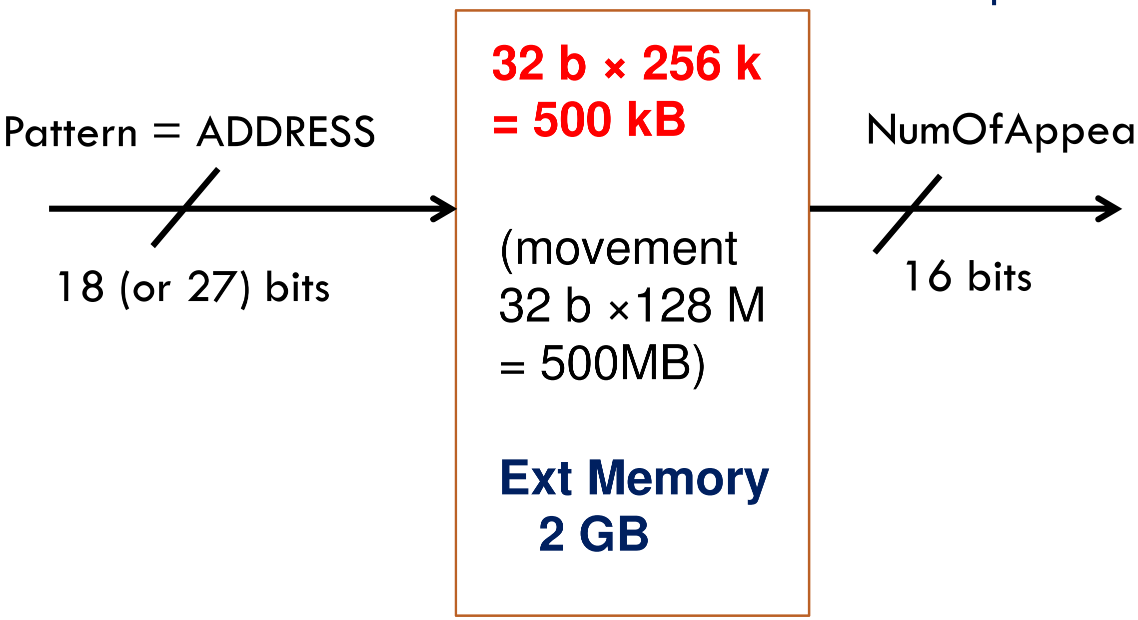
Pattern Selection Process



Calculate the frequency of each possible pattern

4 Gray levels  2^{18}= 256 Kpatterns (B/W movement: 2^{27}= 128 Mpatterns)

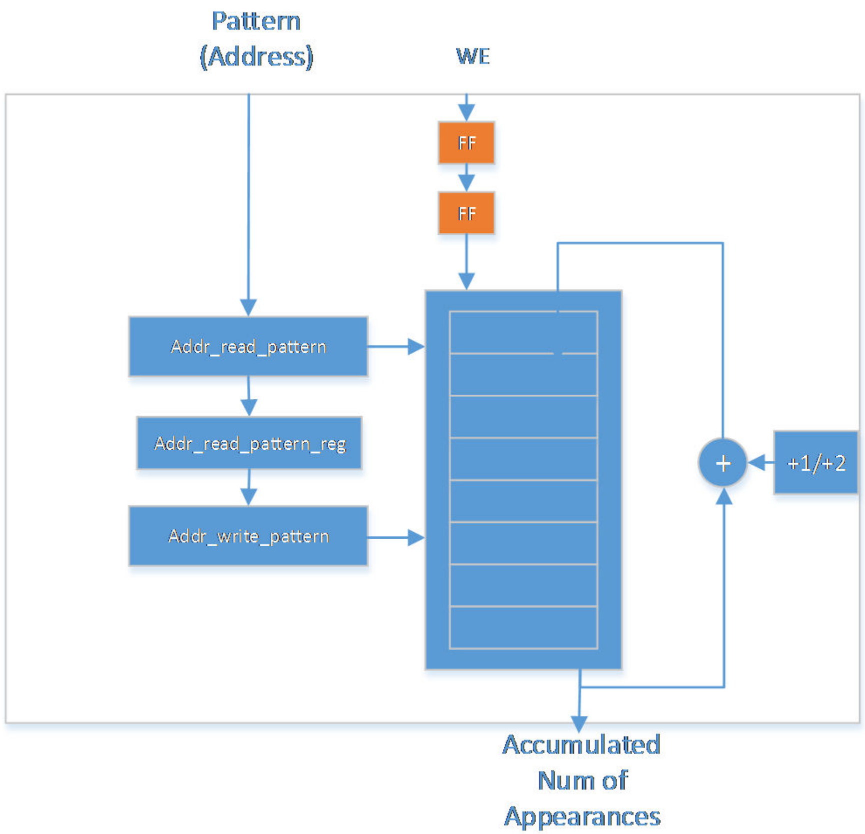
i. e. pattern = 11,11,11-11,11,11, 01,11,11
Each pattern = its own address



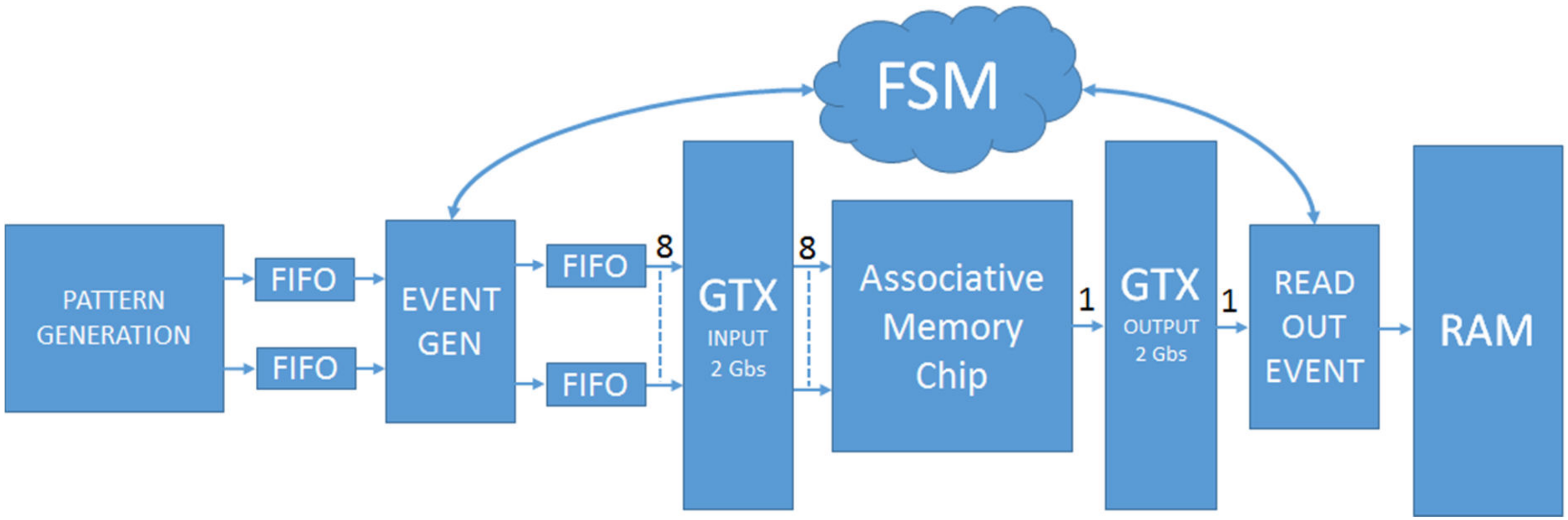
Each Location contains the updated number of appearances of each pattern. When a pattern is identified the specific pattern address is read, contents are increased by one (+1), and written back in the same location - **ACCUMULATION**

Calculate the frequency of each possible pattern

- The Accumulator is optimized to have a throughput of one pattern address per cycle **even if the address is the same as the previous one** (special design to avoid data corruption)



Pattern Matching Phase

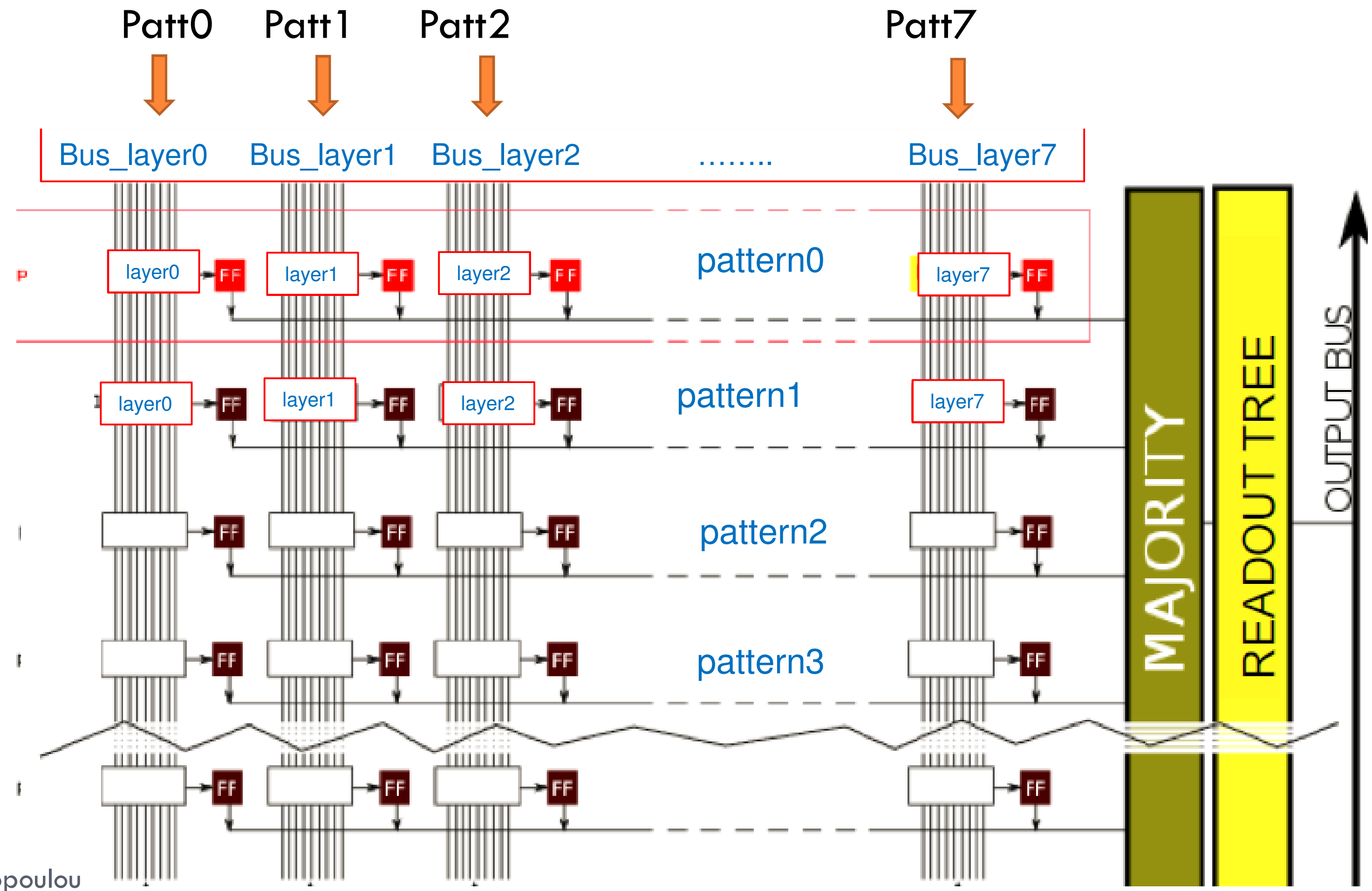


Pattern Matching Phase

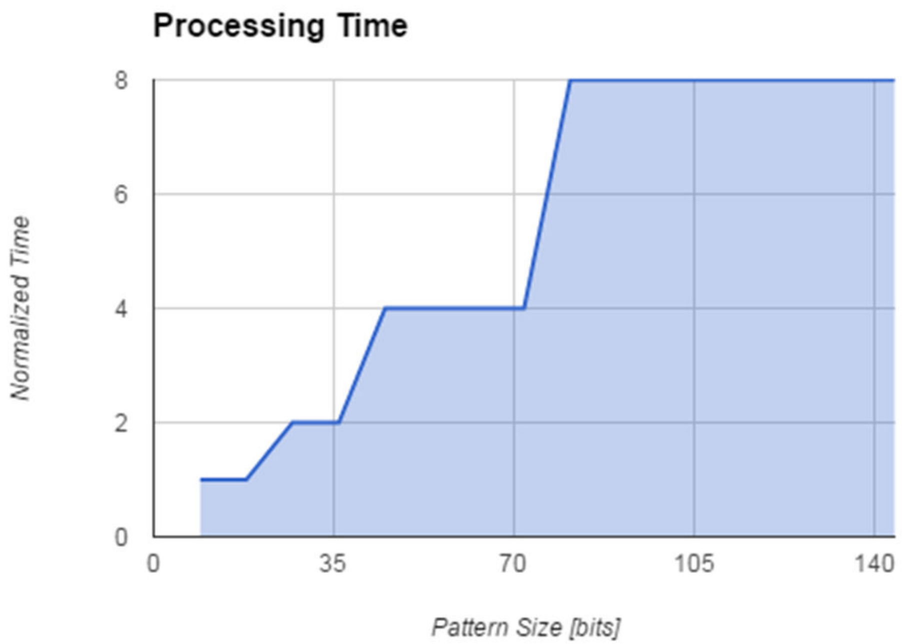
4 grey levels → $256\ kpatterns \rightarrow \sim 1\%\ good\ kpatterns = 2\ kpatterns$

GOOD for AM05 used with threshold 1 – same pattern written 8 times in the 8 columns

Each comparison we **(1)** compare 8 patterns **(2)** read for each match the bitmap **(3)** give INIT



Event Processing Time



Pattern Size [bits]	# OF PATTERN EACH EVENT
9 → 18	8
27 → 36	4
45 → 72	2
81 → 144	1

Medical Image Processing

- Use the filter for Segmented GM identification for an input to a Support Vector Machine classification method