BNL Instrumentation Seminars

BROOKHAVEN NATIONAL LABORATORY

March 23rd, 2005

Advanced Digital Signal Processing in PET
Time-Stamp & DOI

Jean-Baptiste Michaud, eng., M.Sc.

On Behalf of the
GRAMS and LabPET Research Groups

Financed in part by NSERC CRSNG

CMC SCM

CIMF CENTRE D'IMAGERIE MÉTABOLIQUE ET FONCTIONNELLE
CENTRE DE RECHERCHE CLINIQUE
CENTRE HOSPITALIER UNIVERSITAIRE DE SHERBROOKE
Affilié à l'Université de Sherbrooke

Advanced Molecular Imaging

GMS GRAMS BIOMÉDICAL

CIHR IRSC Canadian Institutes of Health Research / Instituts de recherche en santé du Canada

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Very special thanks to Jean-Daniel Leroux, François Bélanger, Catherine Michelle Pepin, Roger Lecomte & Réjean Fontaine for providing some of the figures presented here.

General Outline

1. Presentation of Sherbrooke's PET Research
   - Structure of the LabPET^{tm} Scanner
   - Purpose of Digital Signal Processing

Advanced Processing Methods

2. Neural Networks for Detection Time-Stamping
3. Identification & Vector Quantization in Crystal Identification

Future Developments

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Part 1

Preliminary Considerations
&
Introduction Material

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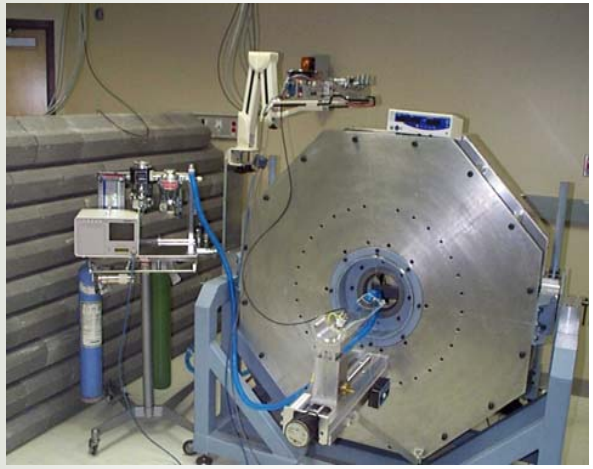
History of Sherbrooke Small-Animal PET Scanners

- Roger Lecomte, Ph.D.
- Built first APD-based scanner in mid-90s
- Now building all-digital second generation
- Réjean Fontaine, Ph.D.
- Current team
- The need for advanced signal processing
- JD Leroux
- JB Michaud



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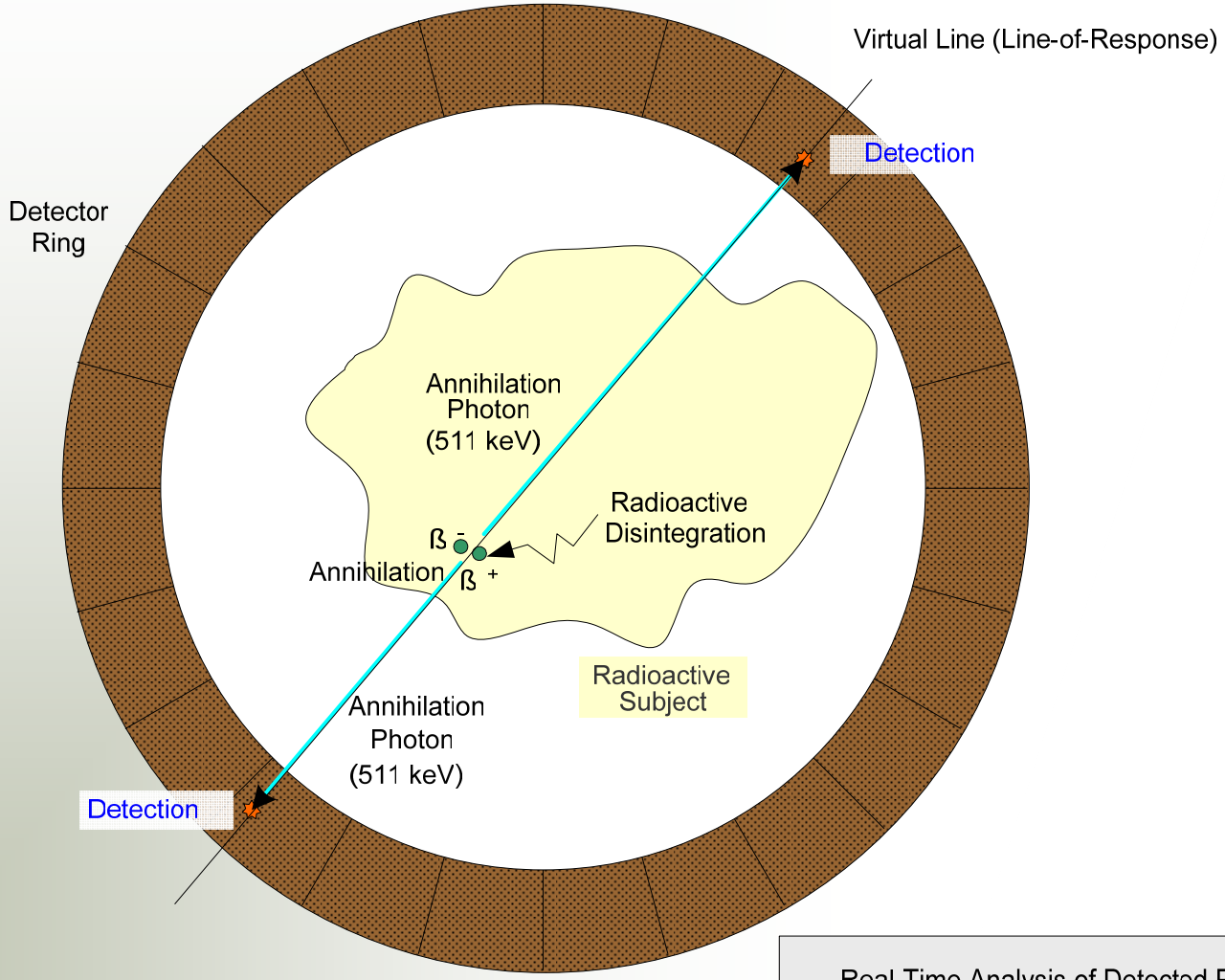
PET Principles

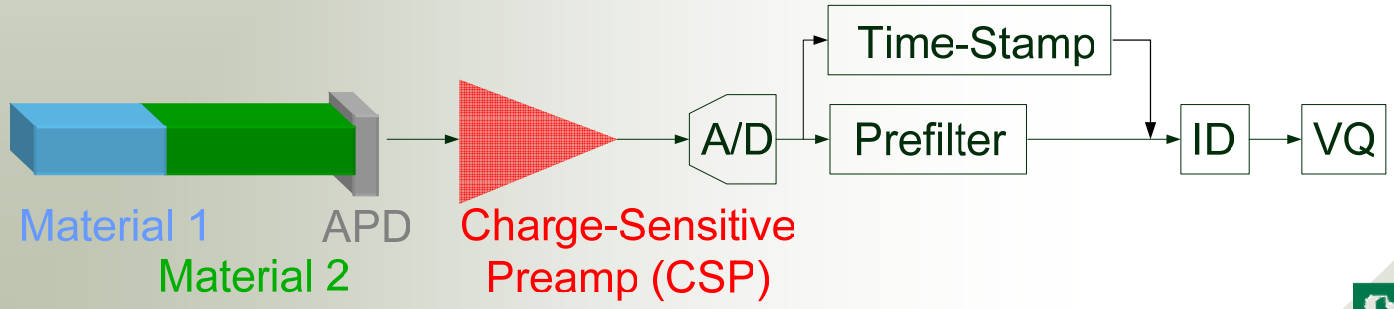


Not to scale

Real-Time Analysis of Detected Photons
Offline Image Reconstruction

All-Digital Scanner

- 4.5- to 6.5-inches FOV
- 0.18µm CMOS low-noise CSP
- Digital conversion at 100 MSPS (research) or 45 MSPS (commercial)
- No analog processing except for preamplification
- Accommodates various stackups and juxtaposition of crystal materials



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Pros & Cons of APD Digital Architecture

- Integration
- Flexibility
- Size
- Diagnostics
- Per-channel data acquisition & calibration
- Research reconfiguration
- Field upgradeable
- Electronics roadmap

+

- Computing power
- Still more expensive
- APD ► Noisier, less gain
- High-density
- Mixed-signal design
- Thermal management

-

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The Need for Advanced Signal Processing

- Beyond the analog-to-digital transposition…
- Possible complexity
- Possible performance

- Adaptation of existing algorithms
  - Functional transposition & modification
  - Change of working hypotheses
  - Simplification

- New algorithms

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Part 2

Signal Processing for Time-Stamp Processing

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Time-Stamp Outline

- Time-stamping goals
- Artificial neural networks
- A neuron behaviour
- Layered structure
- Training

- Application in time-stamping
- Optimal structure
- Results

Objectives

- Be able to minimize coincidence window
- Goal: lower number of random photons treated falsely as true coincidence
- Goal: lower time-stamp uncertainty

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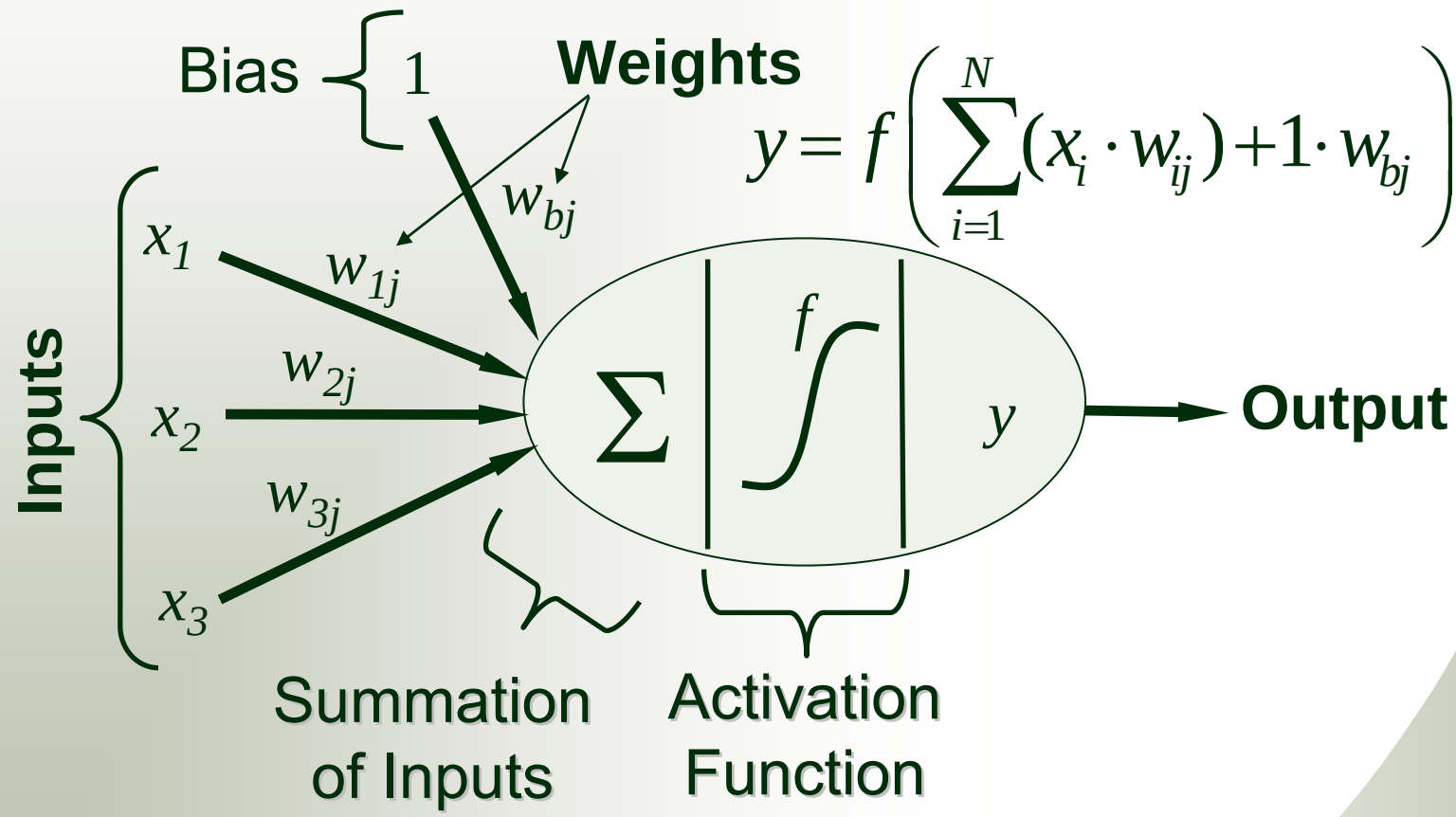
Why Neural Networks?

- Time-stamp is used as a relative measure for the time of detection
- Time-stamp resolution & coincidence resolution (roughly convolution of 2 time-stamp curves) depend on crystal statistics & system noise

- Neural networks can learn from data sets; they can then “infer” better when shown same, but noisy, data
- Per-channel compensation

Neuron Behavior



$$y = f\left(\sum_{i=1}^{N}(x_i \cdot w_{ij}) + 1 \cdot w_{bj}\right)$$

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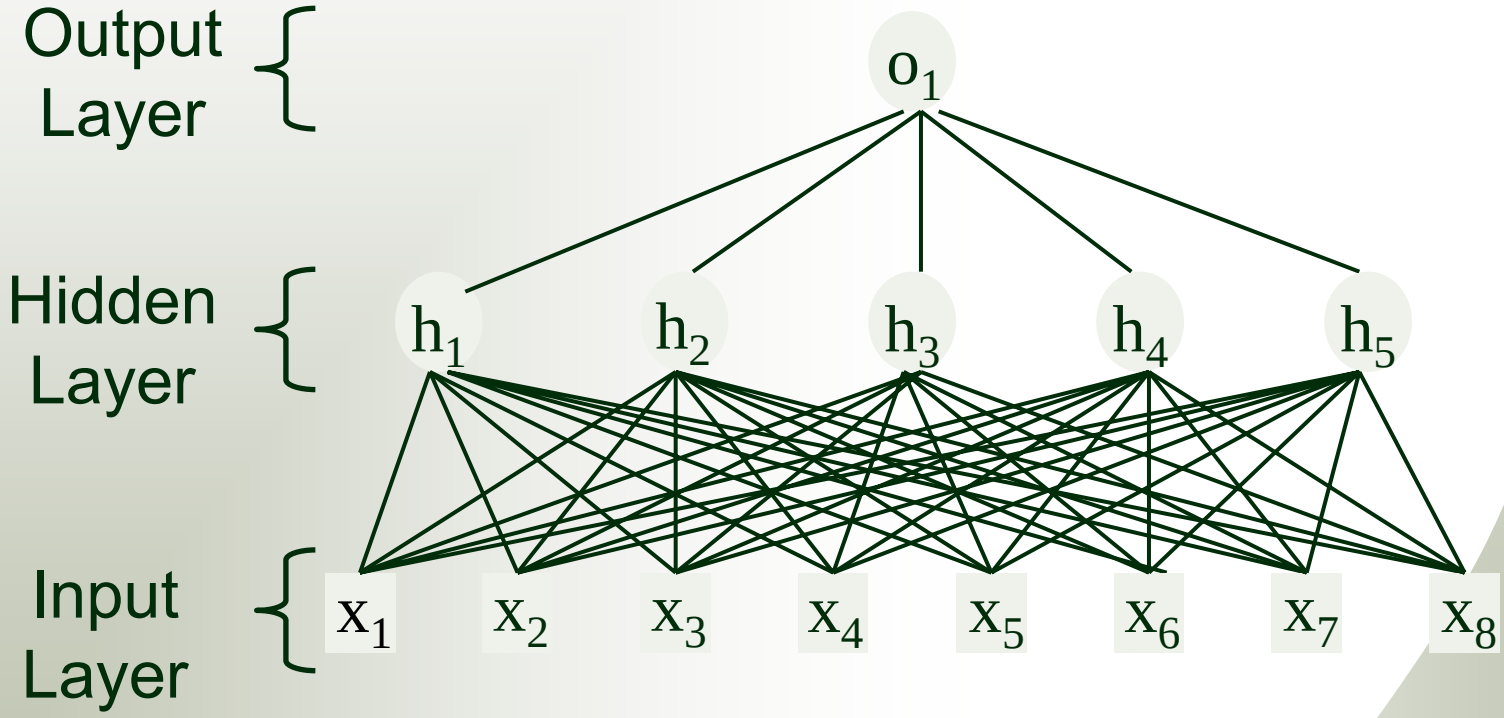
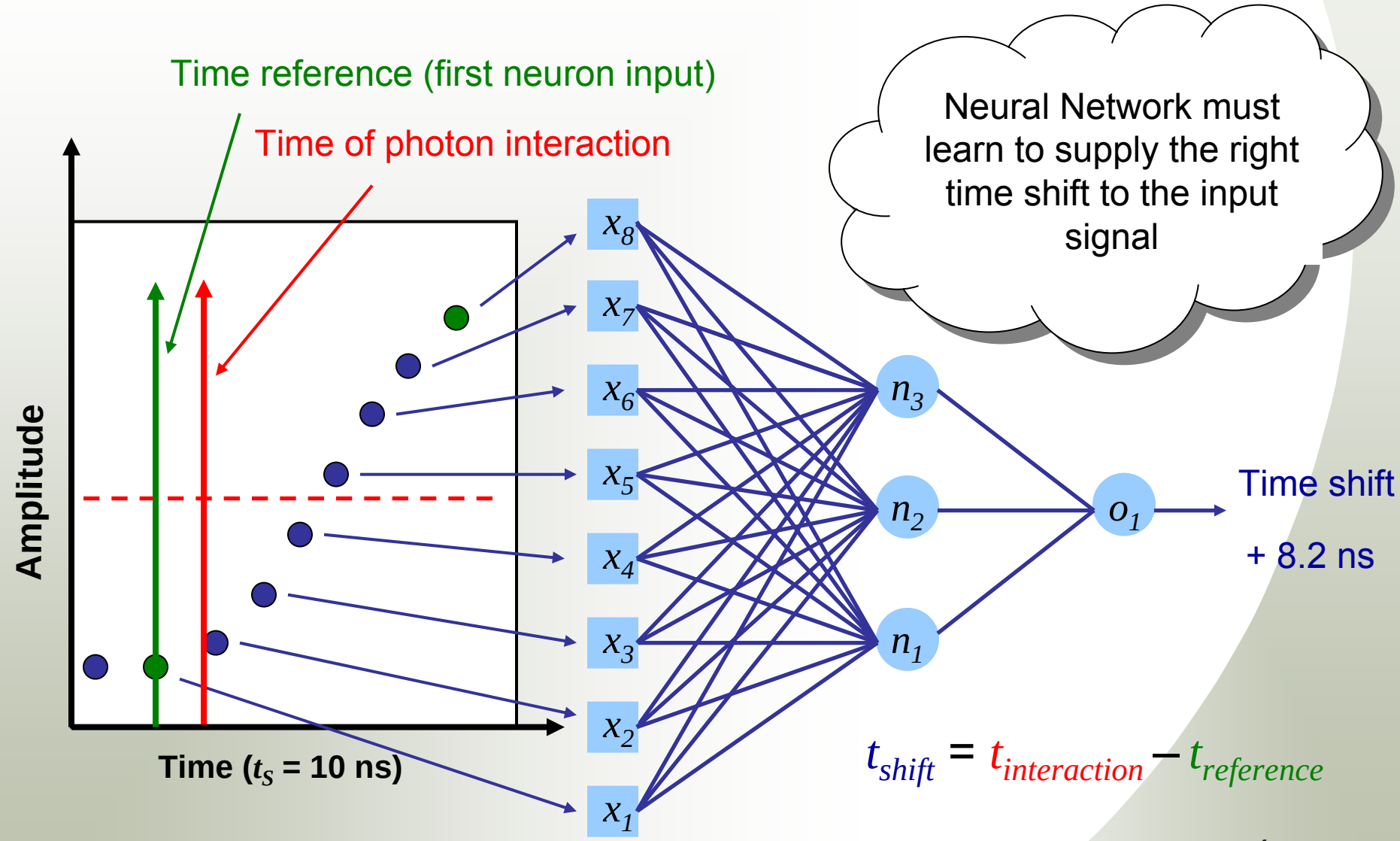
Layer Disposition



How to Encode Data



Neural Network must learn to supply the right time shift to the input signal

$$t_{shift} = t_{interaction} - t_{reference}$$

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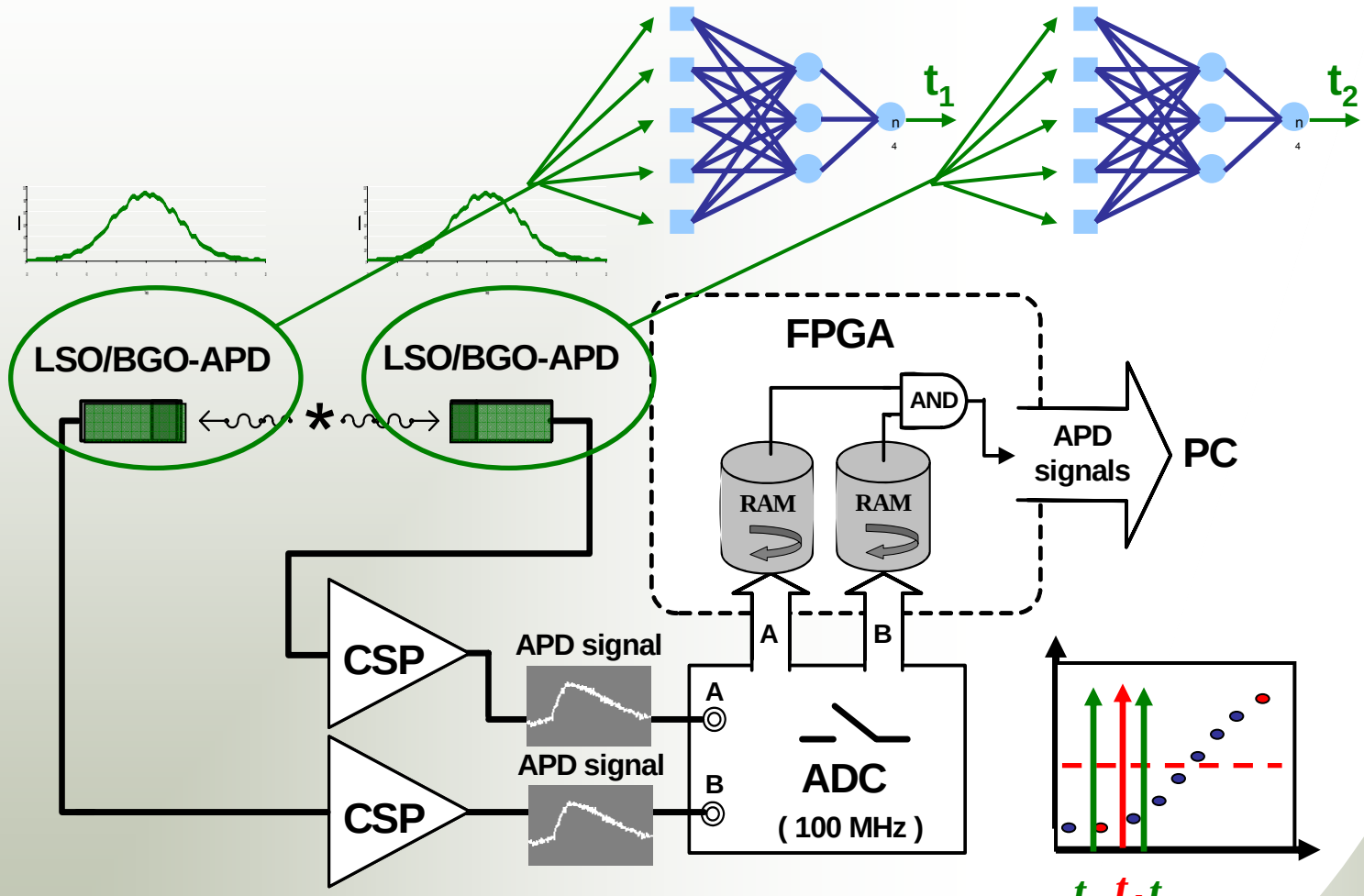
Use in PET Time-Stamping



$(t_1 + t_2) / 2 = t_d$ Averaged time of interaction

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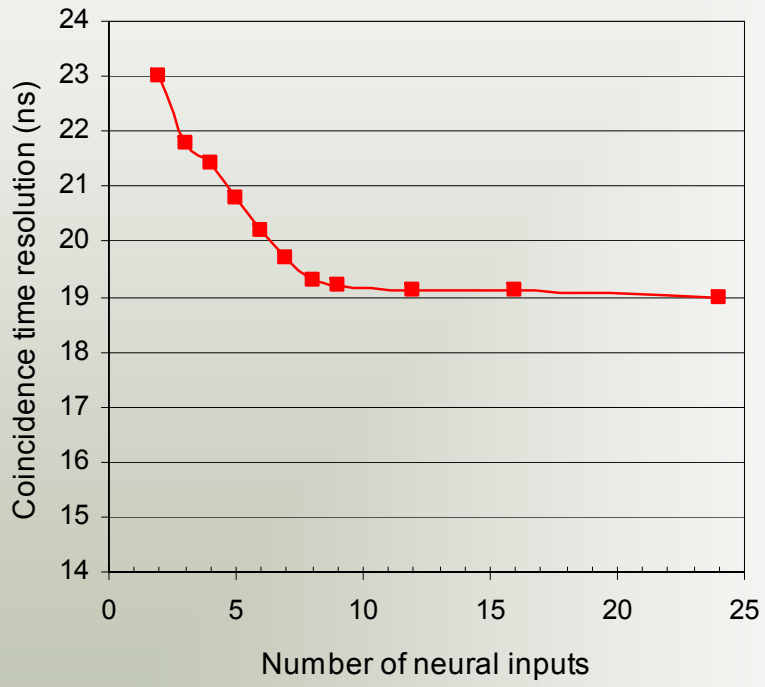
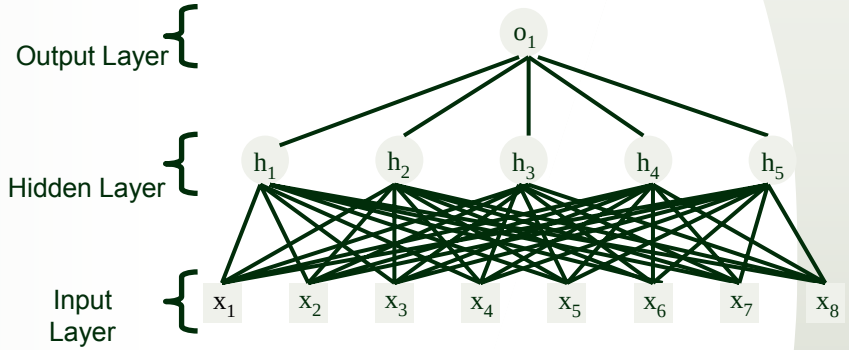
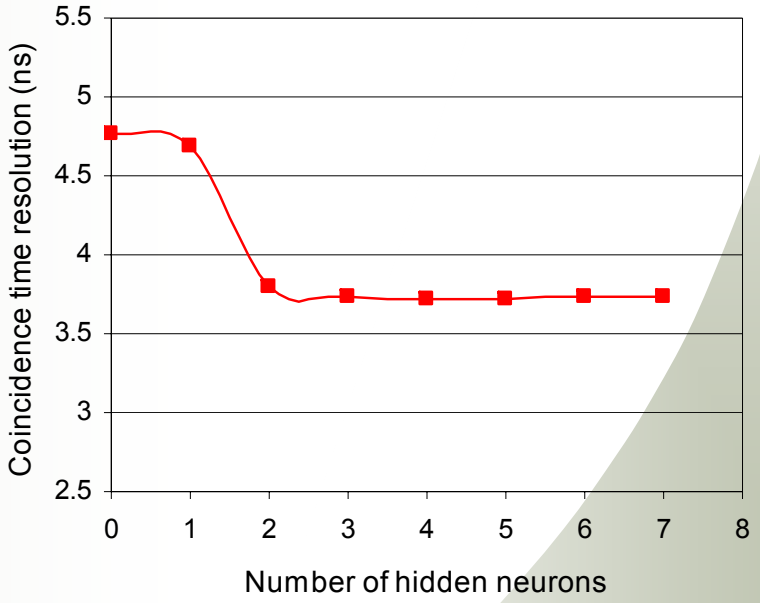
Determination of Minimal Structure

Typical curves used in structure tailoring







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Results

Coincidence time resolution comparison between analog CFD, digital transposition of CFD and neural networks:

- DCFD always better than ACFD
- Improvement is greater for slower materials
- Neural networks slightly better than DCFD in most conditions

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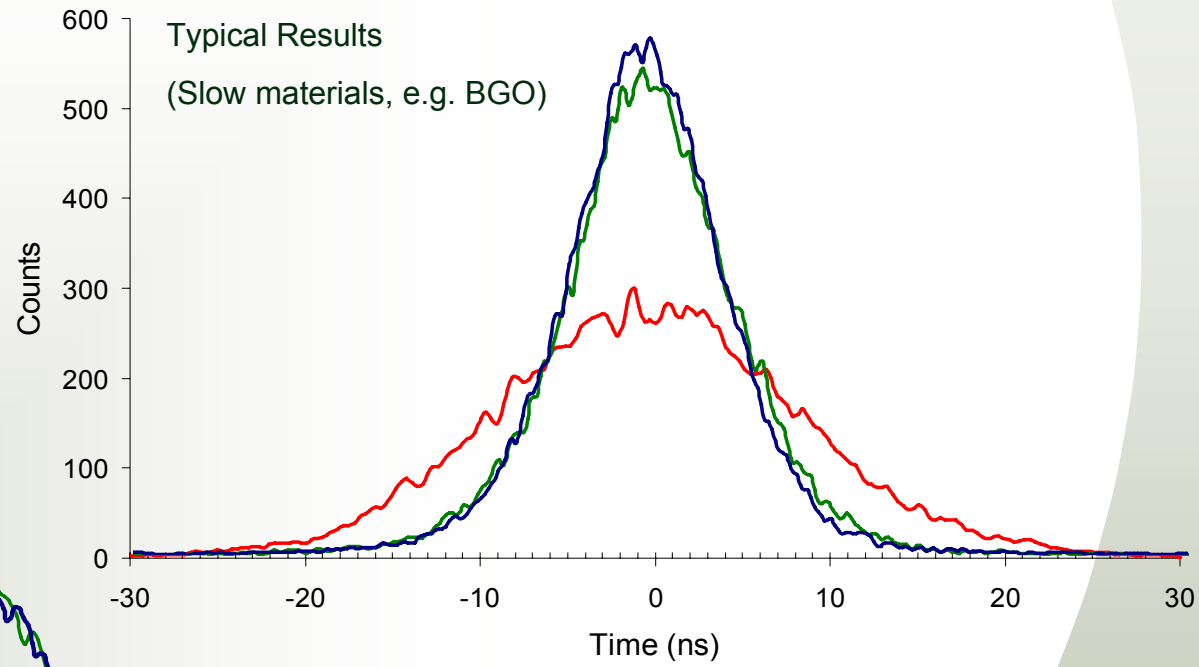
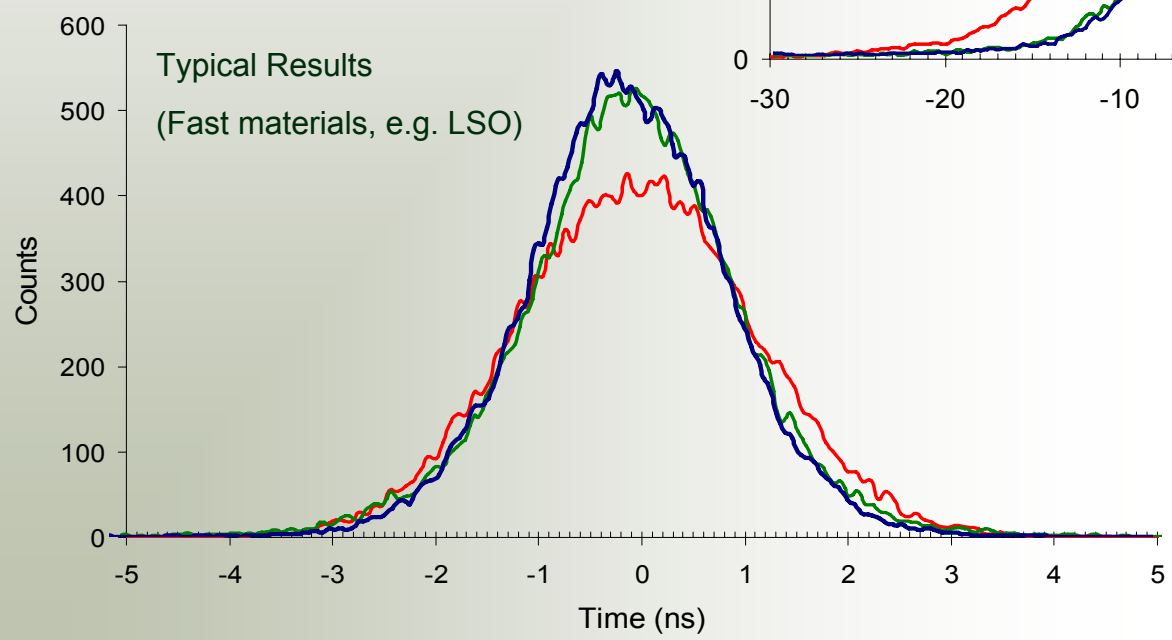
Results (continued)

Analog CFD (τ_s=50 ns)

Digital CFD

Neural Network (8 inputs)





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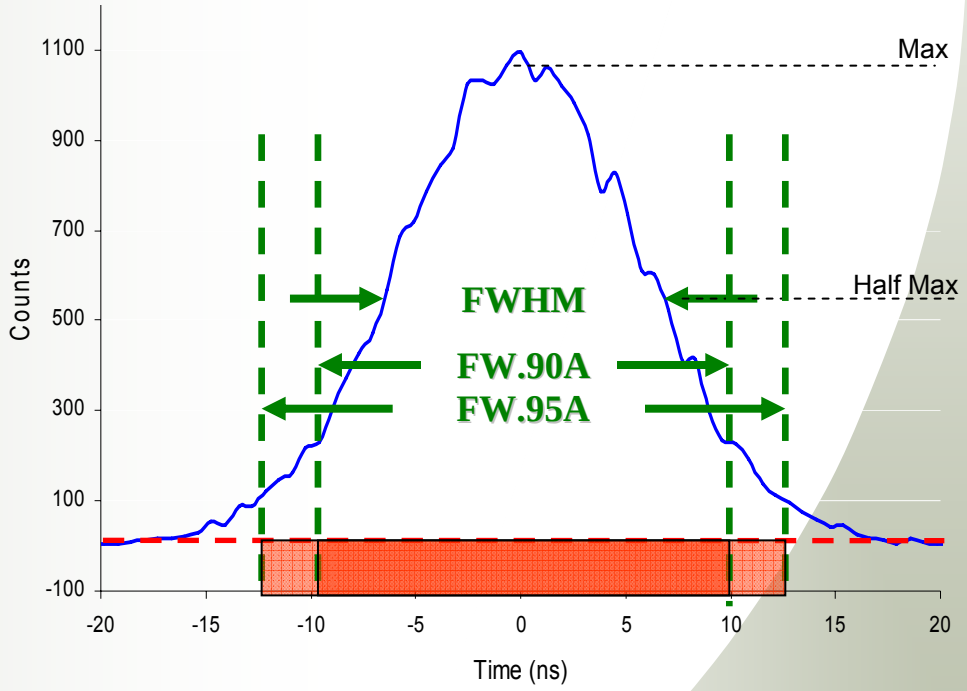
Results (continued)

Crystal	Analysis Method	Coincidence Time Resolution	
		FWHM (ns)	FW.95A (ns)
BGO	Analog	17.5	35.6
	Digital	10.5	21.6
GSO	Analog	7.9	16.6
	Digital	6.1	12.8
LSO	Analog	2.1	4.2
	Digital	1.8	3.5
LYSO	Analog	2.5	4.9
	Digital	2.2	4.2



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Part 3

DOI
Signal Processing

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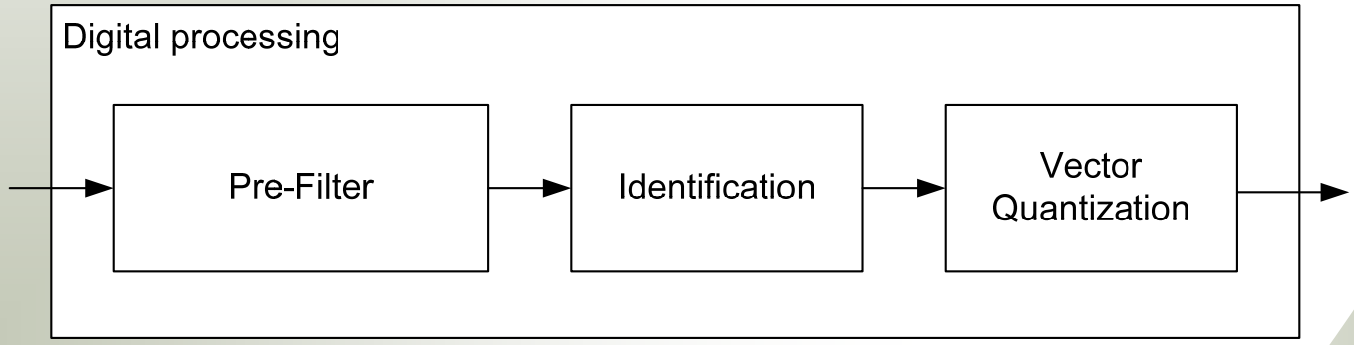
DOI Outline

- DOI goals
- Identification
- Vector Quantization

- Ideal & Phoswich Results



Objectives

- Be able to differentiate scintillation materials with very similar time constant with very low probability of error
- Goal: use phoswich stackups with only new, fast materials (LSO, GSO, LYSO, LGSO)

- Be able to analyze Compton-scattered photons as well
- Goal: maintain low probability of error in heavy noise

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DOI Roadmap

- Model the system
- Simplify the model

- Choose an identification algorithm
- Adapt the identification algorithm

- Choose a vector quantization algorithm

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What is Identification?

- Derived from System Command & Control
- Serves there to build a system model from measured data
- Can be regarded as a complex curve-fitter

- Can map into complex-frequency-space
- Can map onto model with explicit noise representation
- Can be transposed here

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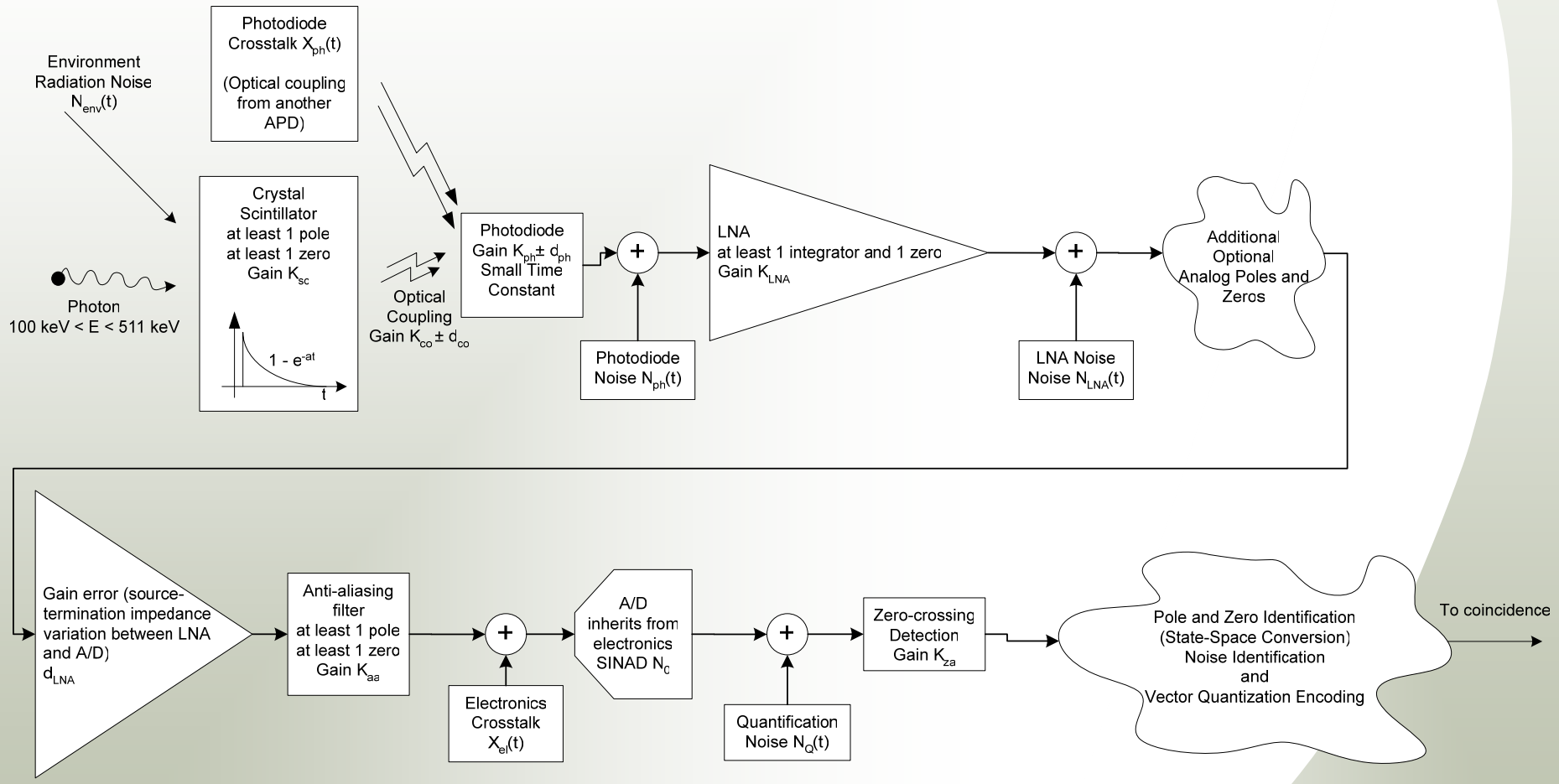
System Model



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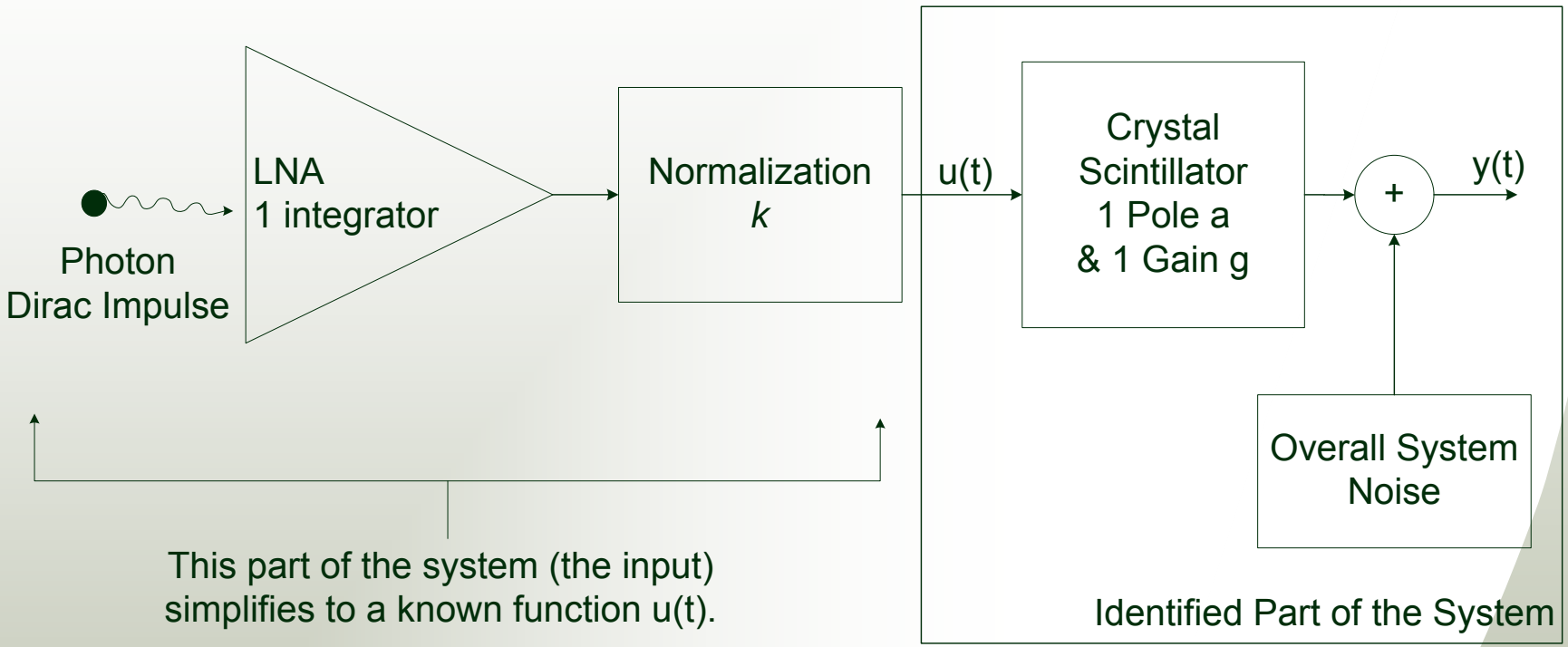
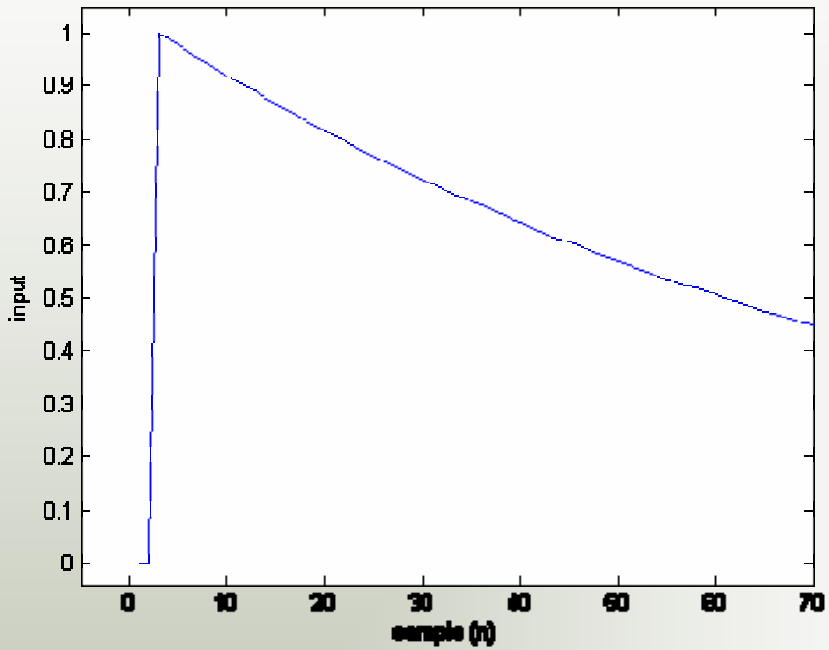
Simplified System Model



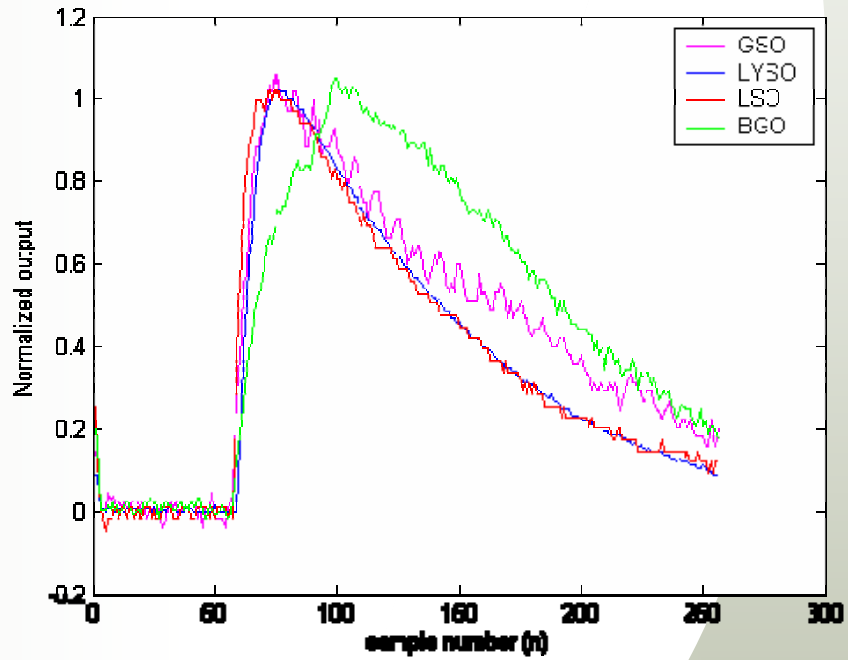
$$y(t_k) + \hat{a}(t_{k-1}) \cdot y(t_{k-1}) = \hat{g}(t_{k-1}) \cdot u(t_{k-1}) + \hat{n}(t_{k-1}) \cdot \varepsilon(t_{k-1})$$

Simplified Model – Signal Perspective

Known Input $u(t_k)$



Measured Signal $y(t_k)$



Model

(fits u into y)

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Algorithm Candidates

- Linear regression
- Least-squares (quadratic criterion)
- Least-squares (gradient criterion)
- Least-squares (adaptive gradient)

- Instrumental variable
- Wiener – Kalman filters

Other Design Selections

Gradient criterion

- Prediction error
- Output error
- …

Implementation details

- Recursion
- Pseudo-inverse
- …

Final Algorithm

$$y(z^{-1}) = \frac{G \cdot u(z^{-1}) + c \cdot \varepsilon(z^{-1}) \cdot z^{-1}}{1 + a \cdot z^{-1}}$$

$$\hat{\theta} = \begin{bmatrix} \hat{a} \\ \hat{G} \\ \hat{c} \end{bmatrix}$$

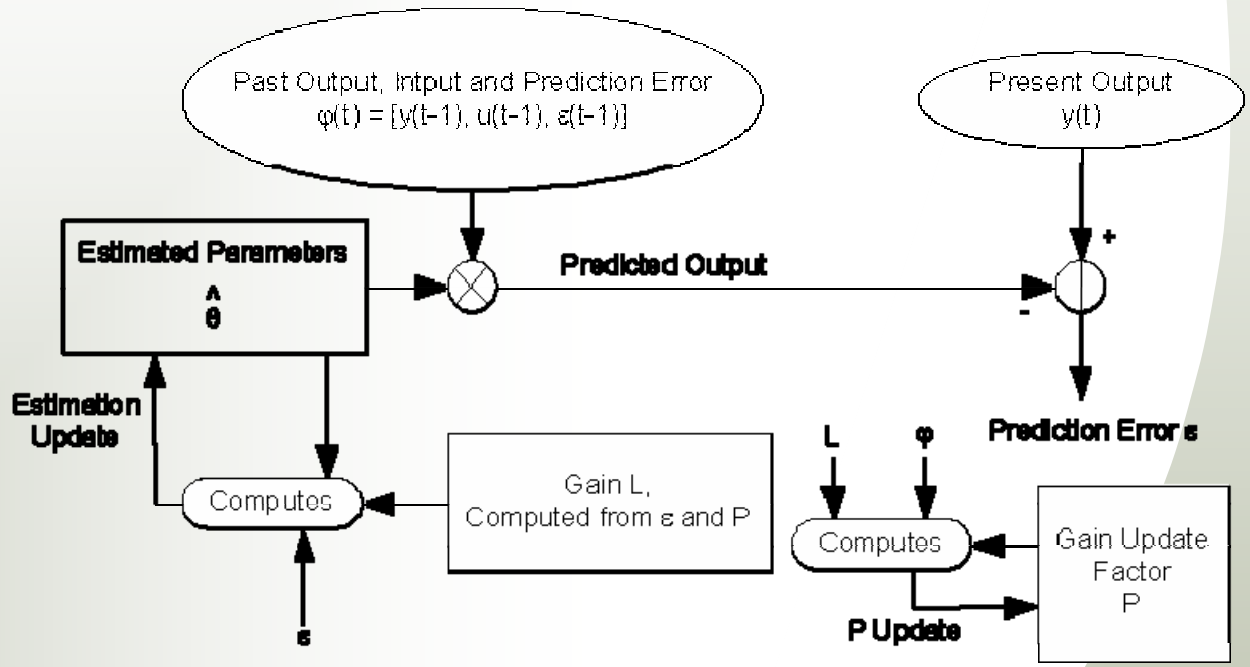
$$\varphi(t) = \begin{pmatrix} -y(t-1) \\ u(t-1) \\ -\varepsilon(t-1) \end{pmatrix}$$

$$\varepsilon(t) = y(t) - \hat{\theta}^T(t-1)\varphi(t)$$

$$L(t) = \frac{P(t-1)\varphi(t)}{1 + \varphi^T(t)P(t-1)\varphi(t)}$$

$$\hat{\theta}(t) = \hat{\theta}(t-1) + L(t)\varepsilon(t)$$

$$P(t) = P(t-1) - L(t)\varphi^T(t)P(t-1)$$



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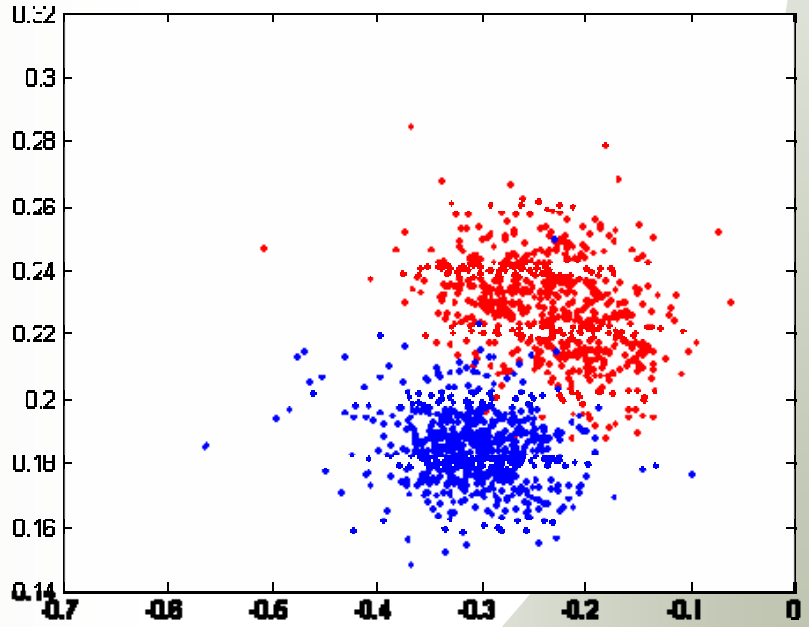
The Need for Vector Quantization

- Identification yields 3 parameters
- 1D or 2D discrimination alone does not suffice for optimal separation
- Need an N-dimension discriminator



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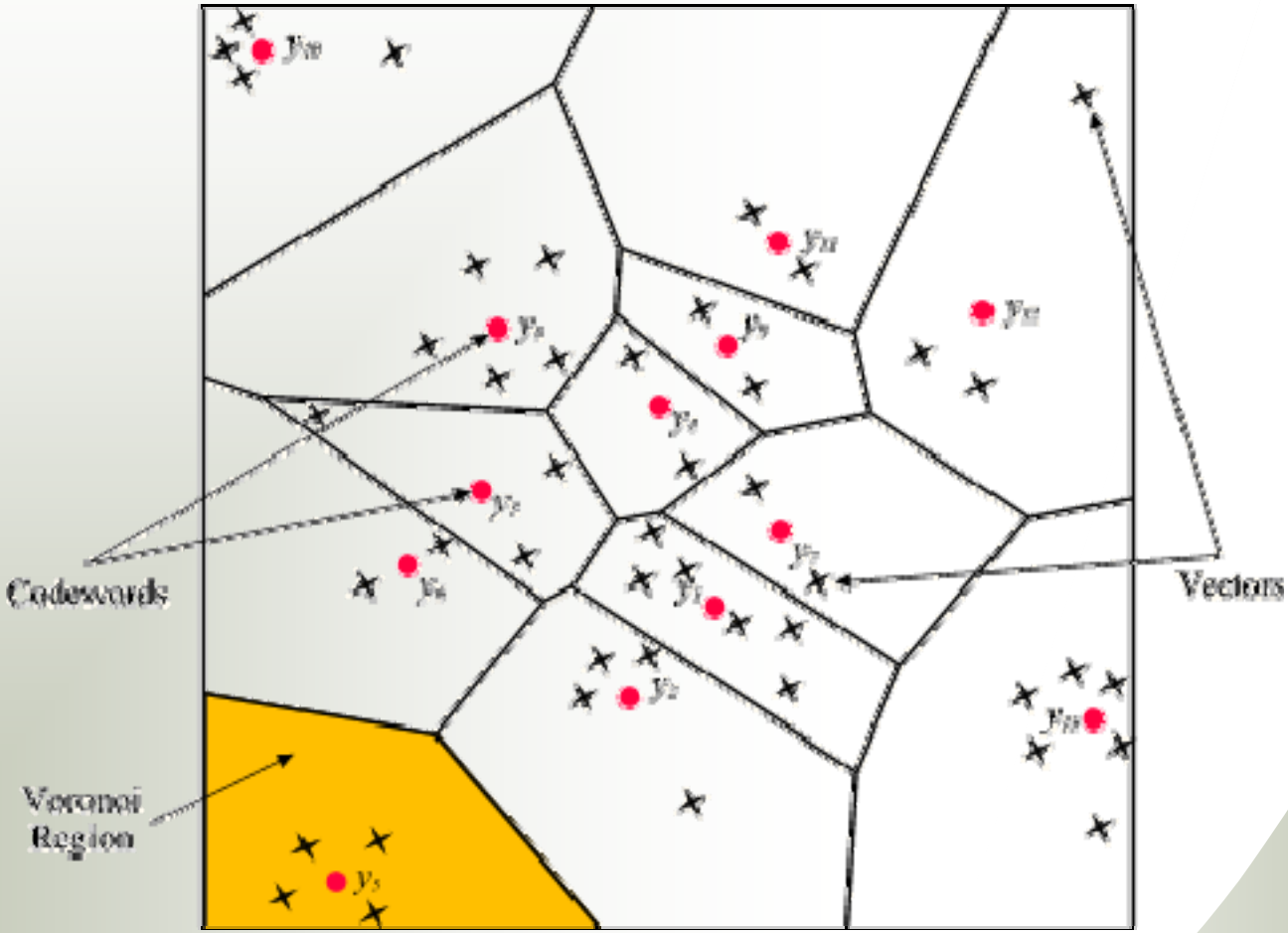
What is Vector Quantization?

- Inputs are called vectors, i.e. a set of coordinates in a N-dimension space
- The space is divided into sub-space representing arbitrary-chosen realities
- Vector quantization chooses to which sub-space a vector belongs, actually quantizing the space

- Hence N-dimension simultaneous discrimination

Graphical Vector Quantization



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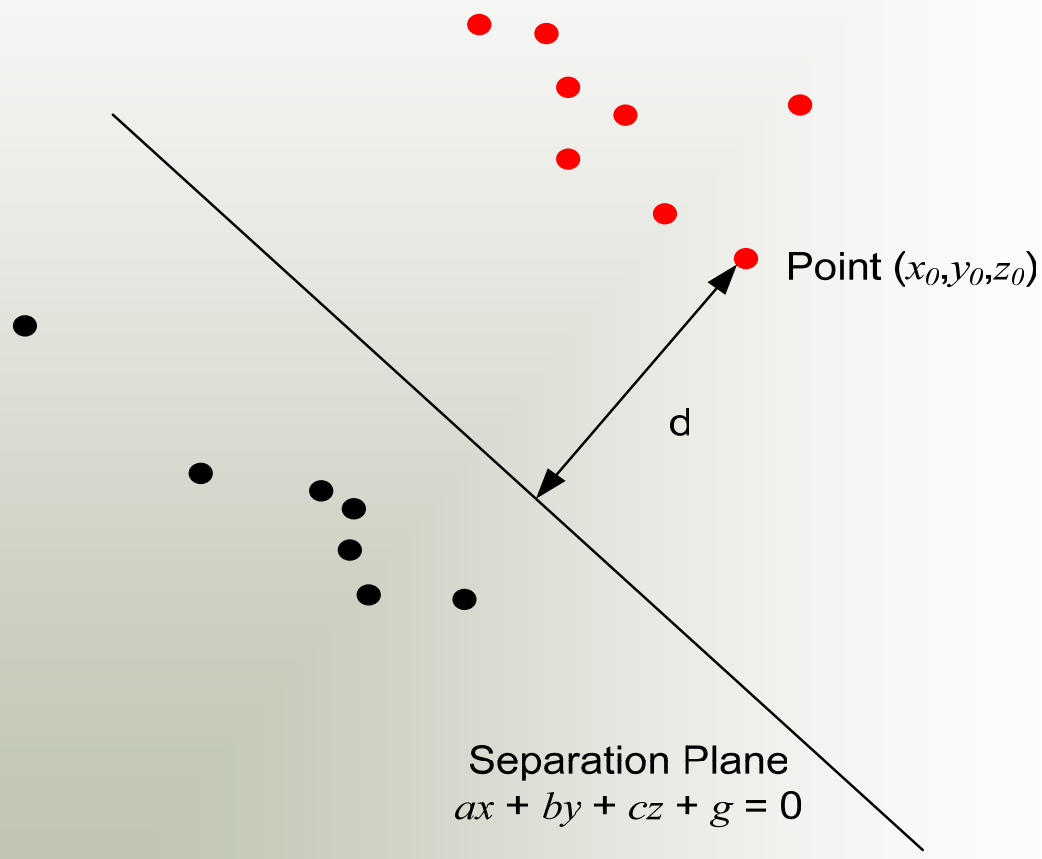
Simplified Vector Quantization



$$d = \frac{ax_0 + by_0 + cz_0 - g}{\sqrt{a^2 + b^2 + c^2}}$$

For 2 materials we only need the sign of d!

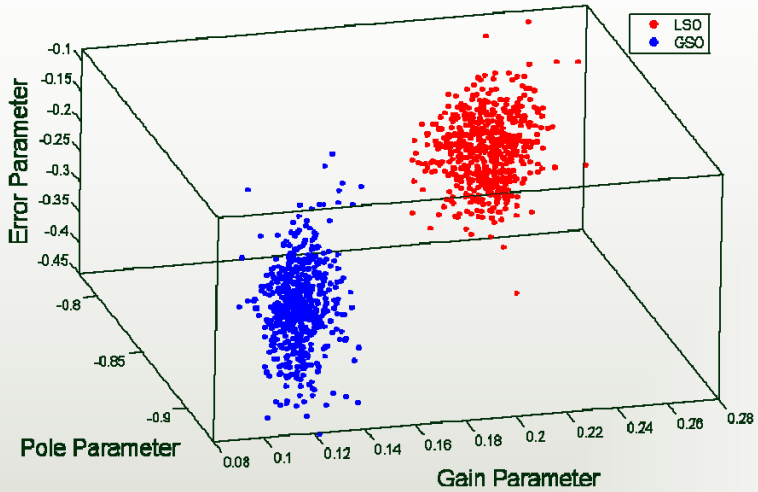
The Ideal & Phoswich Paradigms

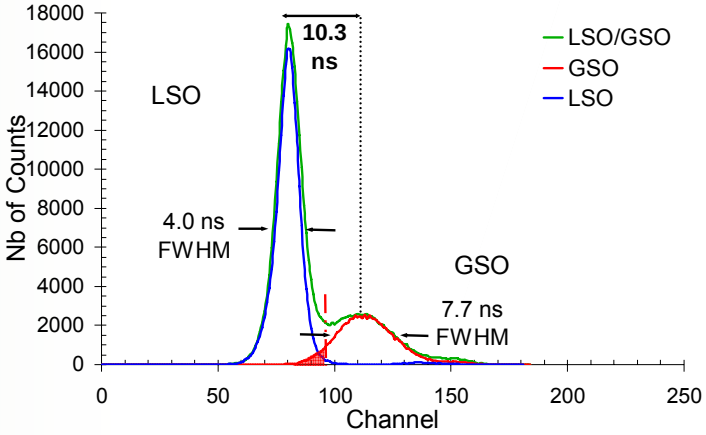
- Usually, all non photoelectric (511 keV) photons are discarded
- When Compton-scattered photon are present, superposition occur

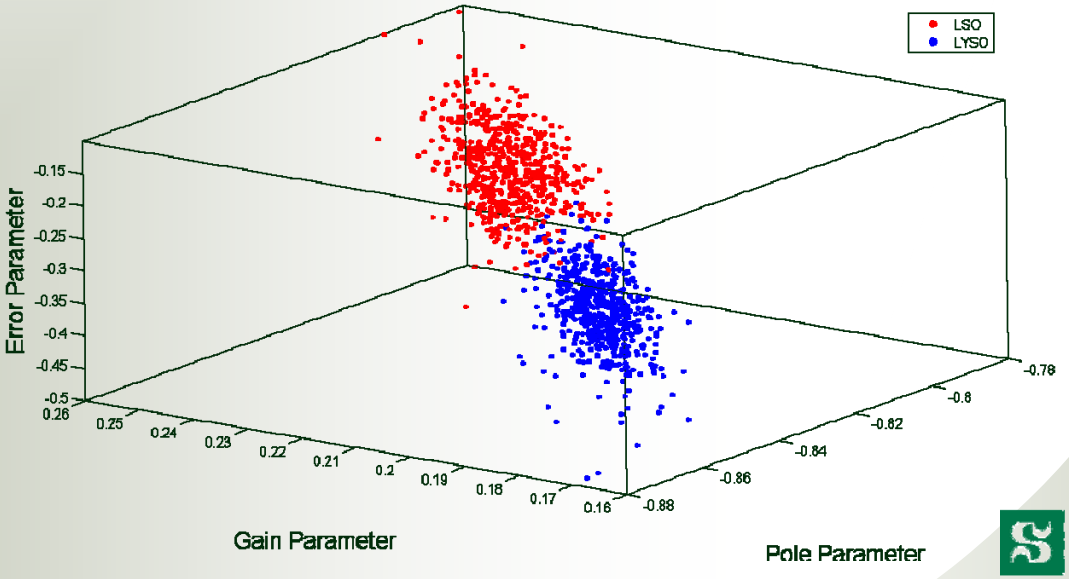
- Also, no “placebo” reference test set

- Ideal: only single material, all >100 keV photons
- Phoswich: all >100 keV photons, stackup

Ideal-Conditions Results







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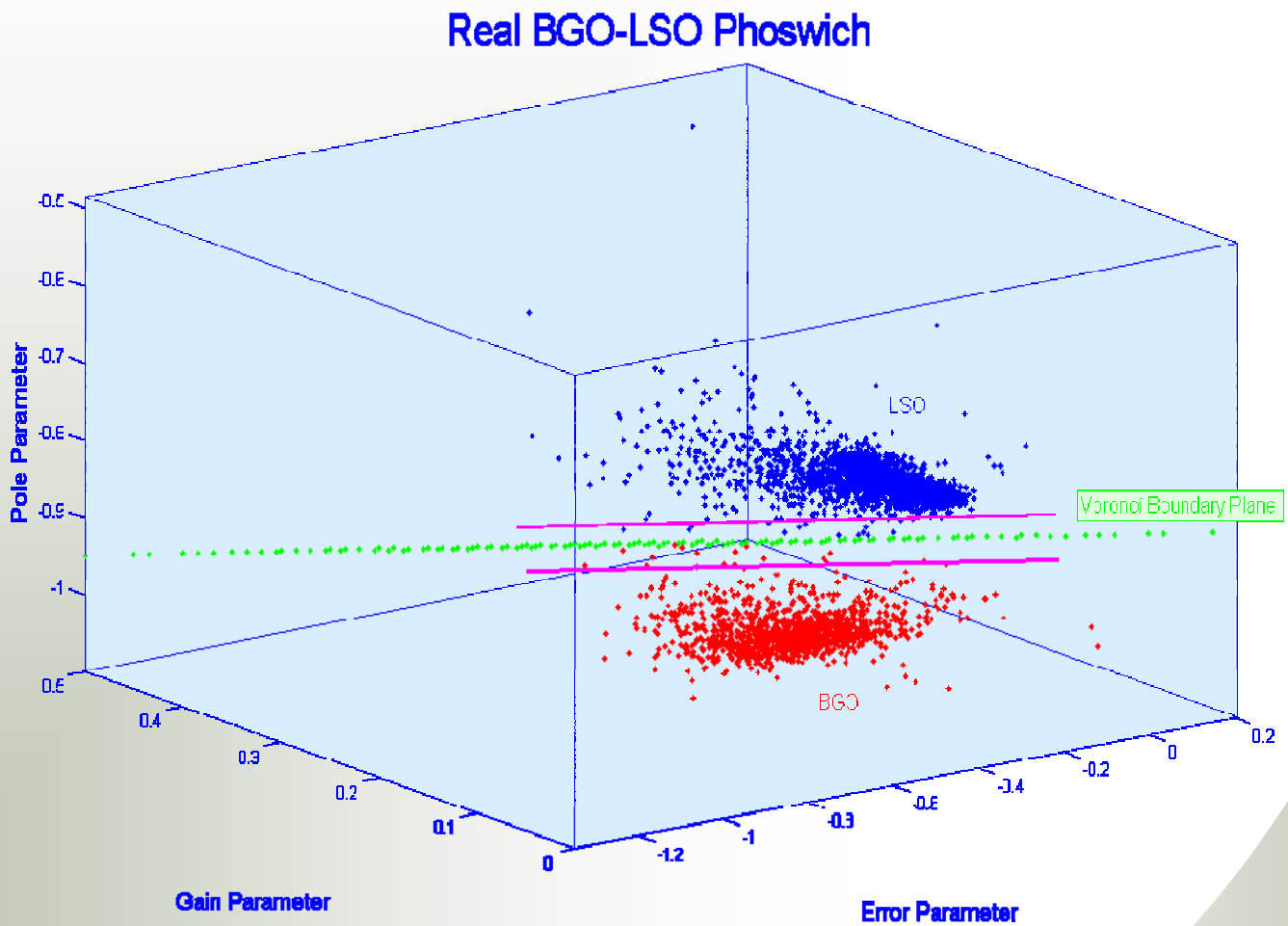
Phoswich-Conditions Results



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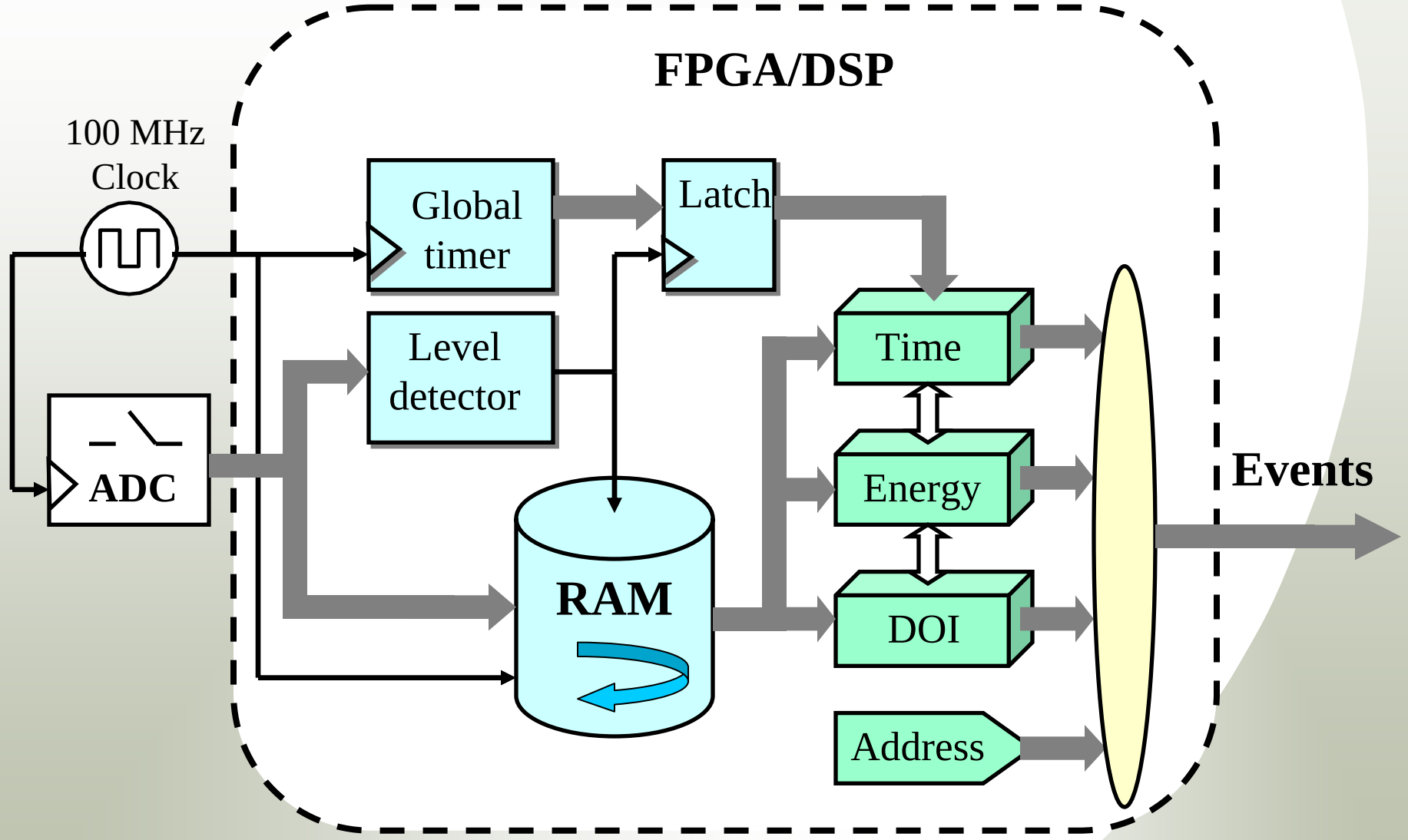
Summary of Results

Materials	Photons	DOI	Error (%)
BGO – all others	150000	ID + QV	0
		PSD	3.5
(L)GSO – L(Y)SO	150000	ID + QV	0
		PSD	8.3
LSO – LYSO (no Compton)	40000	ID + QV	0
		PSD	ND
LSO – LYSO (All photons)	150000	ID + QV	0.5
		PSD	Practically inseparable

- Results are at least one order of magnitude better than traditional PSD in ideal conditions alone.
- ID+VQ independent from amplitude, high properties sensitivity
- ID+VQ can discriminate with minimal error (<3%) in very low SNR (5 dB)

FPGA & DSP Implementation



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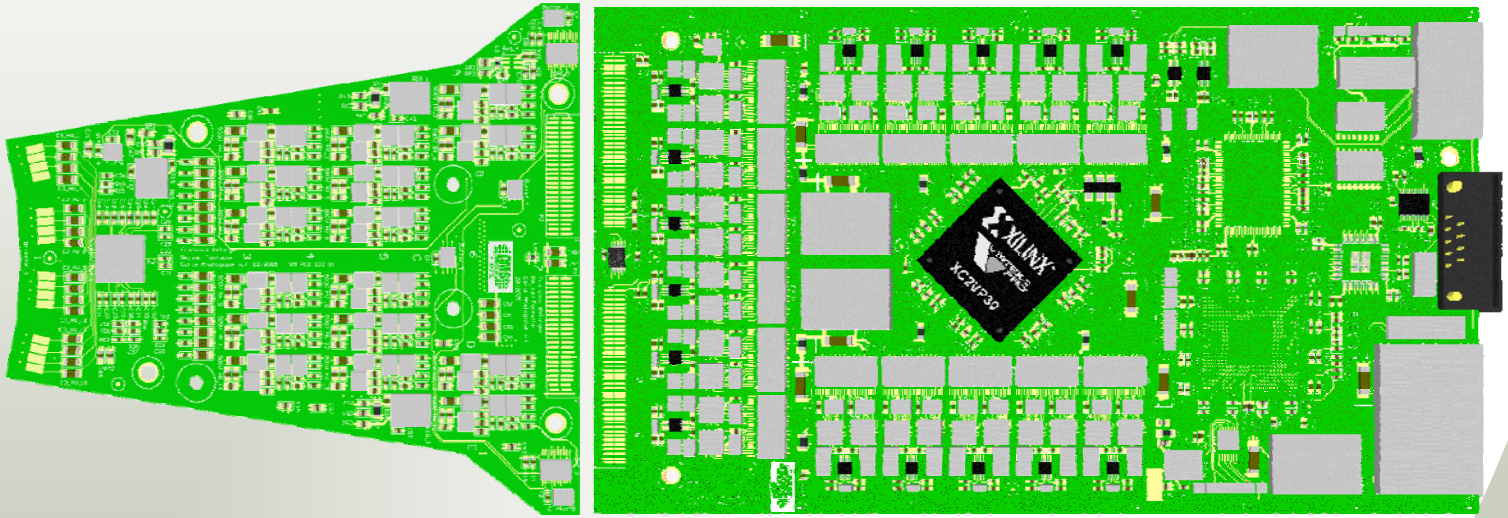
Implementation (Continued)



Next Developments in Signal Processing

- Other time-stamp strategies
- Vector-quantization-only DOI
- Algorithms from other fields
- New algorithms

- New possibilities for improved efficiency through Compton scatter analysis
- Better image quality at lower dose
- PET/CT

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