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HSI payload software (FPGA)

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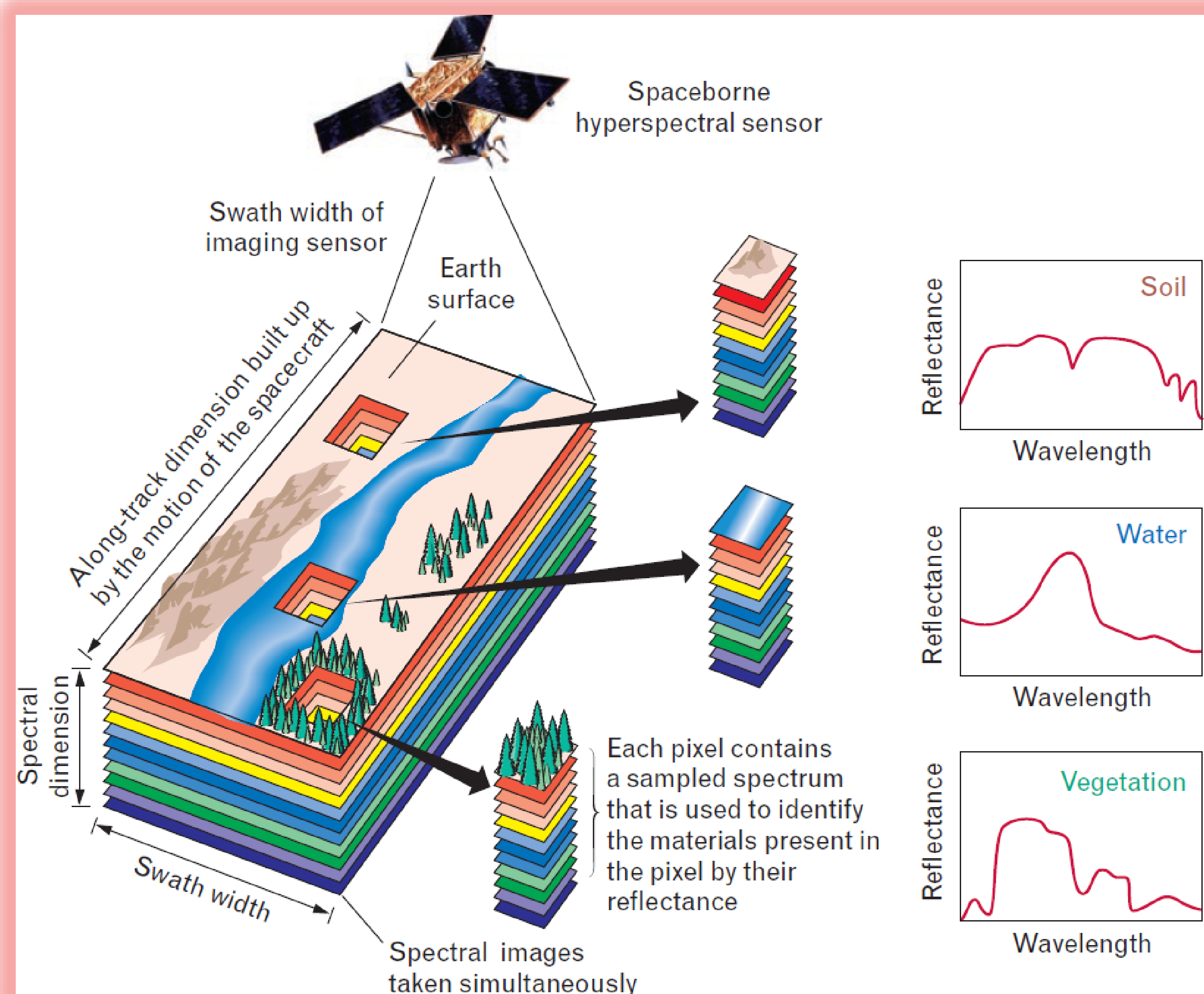
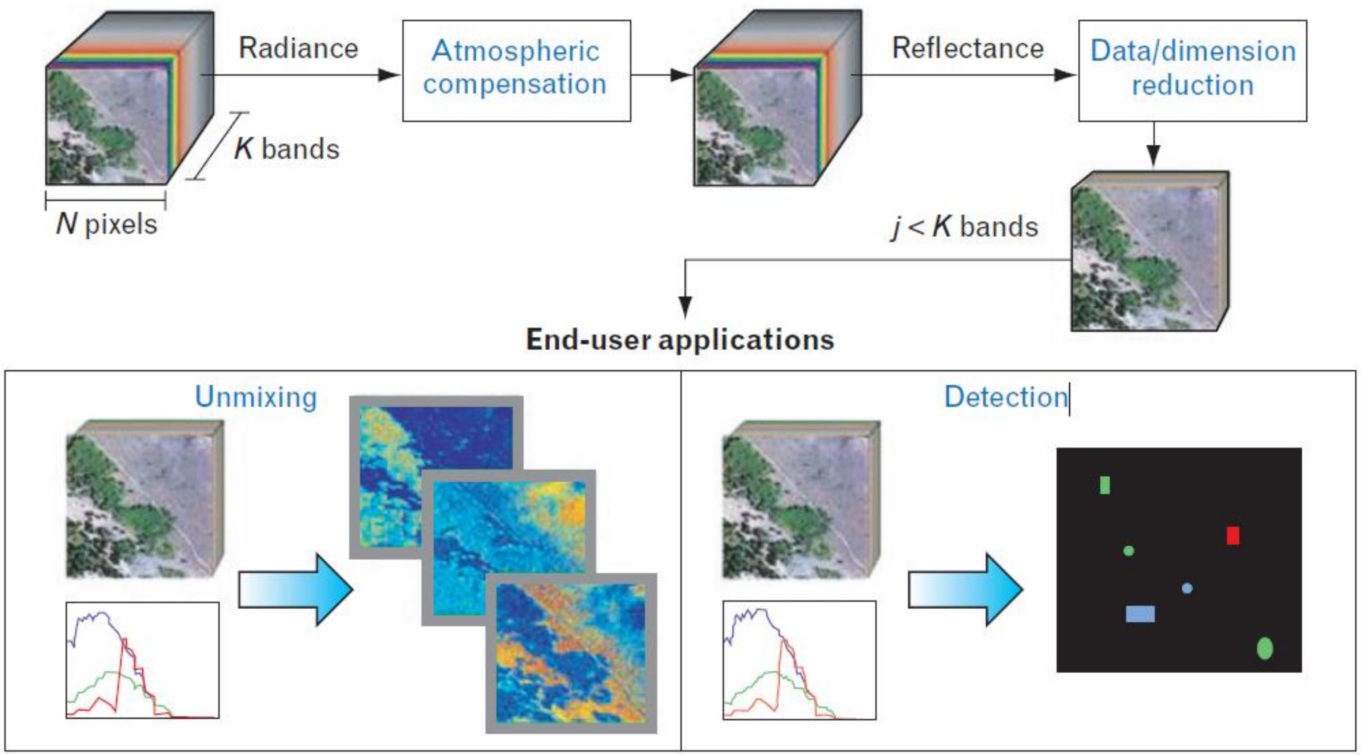
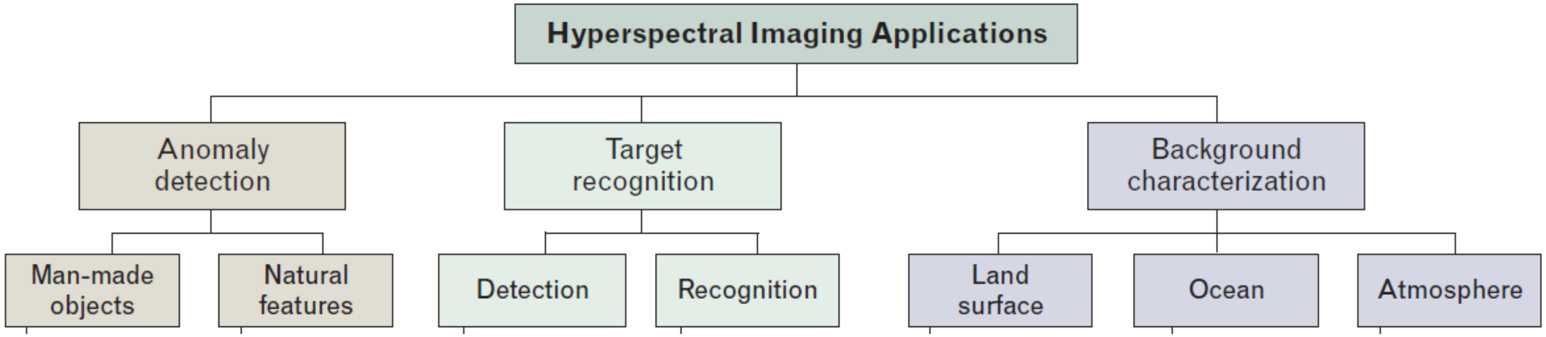
Introduction

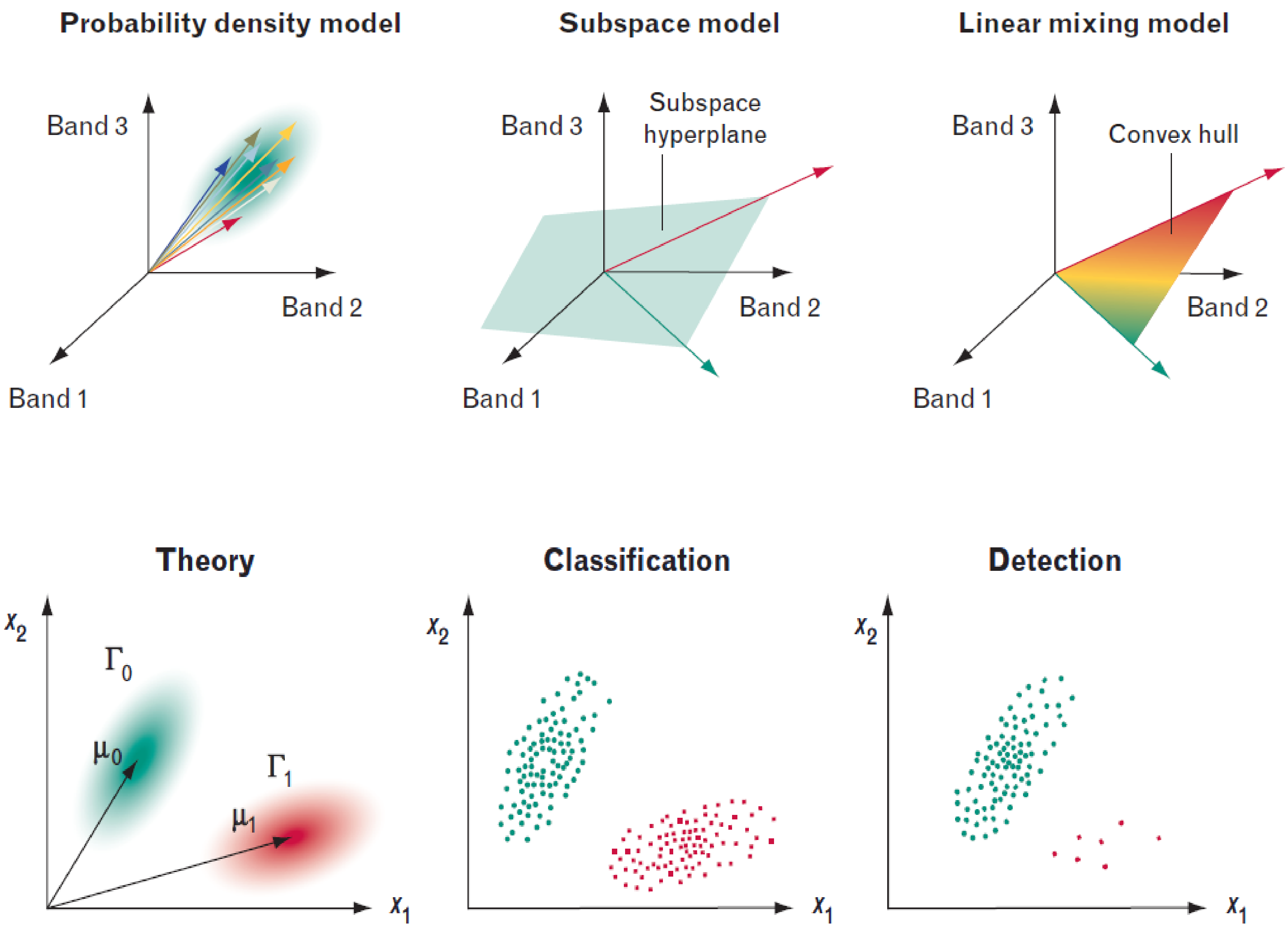


Dataflow in HSI processing





Spectral Variability Models



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Target Detection

CEM, OSP

GLRT, ACE

AMSD, MF

Material Count Estimation

HFC VD

HySime

Dimensionality Reduction

PCA,

MNF, ICA

Anomaly Detection

Reed Xiaoli (RX)

Endmember Finders

ATGP, ICA-EEA,

N-FINDR, VCA,

PPI,

Least Square Solvers

FCLS

NNLS

Spectral Comparison

SAM

SID

Normalized Cross Correlation

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Taxonomy of Hyperspectral Imaging Target Detection Algorithms

	Signal Model	Assumptions	Detector $y = D(\mathbf{x})$	Name	Comments
targets	$H_0: \mathbf{x} \sim N(\boldsymbol{\mu}_0, \boldsymbol{\Gamma}_0)$	Known $\boldsymbol{\mu}_0, \boldsymbol{\mu}_1, \boldsymbol{\Gamma}_0, \boldsymbol{\Gamma}_1$	$(\mathbf{x}-\boldsymbol{\mu}_0)^T\boldsymbol{\Gamma}_0^{-1}(\mathbf{x}-\boldsymbol{\mu}_0) - (\mathbf{x}-\boldsymbol{\mu}_1)^T\boldsymbol{\Gamma}_1^{-1}(\mathbf{x}-\boldsymbol{\mu}_1)$	Bayes or Neyman-Pearson quadratic classifiers	$\boldsymbol{\Gamma} \equiv \boldsymbol{\Gamma}_1 = \boldsymbol{\Gamma}_0 \Rightarrow y = (\boldsymbol{\mu}_1 - \boldsymbol{\mu}_0)^T\boldsymbol{\Gamma}^{-1}\mathbf{x}$ Plug-in detectors: estimate $\boldsymbol{\mu}_1, \boldsymbol{\mu}_0, \boldsymbol{\Gamma}_1, \boldsymbol{\Gamma}_0$

A-priori information	Quantity	Matched filter	Clairvoyant	Adaptive	Anomaly detection
Target subspace	S	Known	Known	Known	Unknown
Target abundance	a	Known	Unknown	Unknown	Unknown
Background and noise covariance	Γ	Known	Known	Unknown	Unknown
Background subspace and noise variance	B, σ_w^2	Known	Known	Unknown	Unknown

	Signal Model	Assumptions	Detector $y = D(\mathbf{x})$	Name	Comments
Subpixel targets		$P = 1 \Rightarrow \mathbf{S} \rightarrow \mathbf{s}$	$\frac{\mathbf{s}^T\hat{\boldsymbol{\Gamma}}^{-1}\mathbf{x}}{(\mathbf{s}^T\hat{\boldsymbol{\Gamma}}^{-1}\mathbf{s})^{1/2}(\psi_1 + \psi_2\mathbf{x}^T\hat{\boldsymbol{\Gamma}}^{-1}\mathbf{x})^{1/2}}$	estimator	$\Rightarrow \hat{\boldsymbol{\Gamma}}^{-1} = \sum_{k=1}^{Q}\frac{1}{\lambda_k}\mathbf{u}_k\mathbf{u}_k^T$
	$H_0: \mathbf{x} = \mathbf{B}\mathbf{a}_{b,0} + \mathbf{w}$ $H_1: \mathbf{x} = \mathbf{S}\mathbf{a} + \mathbf{B}\mathbf{a}_{b,1} + \mathbf{w}$	$\mathbf{w} \sim N(0, \sigma_w^2\mathbf{I})$ $\mathbf{P}_A^{\perp} \equiv \mathbf{I} - \mathbf{A}(\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T$	$\frac{\mathbf{x}^T(\mathbf{P}_B^{\perp} - \mathbf{P}_{SB}^{\perp})\mathbf{x}}{\mathbf{x}^T\mathbf{P}_{SB}^{\perp}\mathbf{x}}$	GLRT detector	CFAR $\mathrm{SINR}_o = \frac{\lVert\mathbf{P}_B^{\perp}\mathbf{S}\mathbf{a}\rVert^2}{\sigma_w^2}$
			$\mathbf{s}\mathbf{P}_B^{\perp}\mathbf{x}$	Orthogonal subspace projector (OSP)	Non-CFAR

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IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 50, NO. 2, FEBRUARY 2012

FPGA Implementation of the N-FINDR Algorithm for Remotely Sensed Hyperspectral Image Analysis

Carlos González, Daniel Mozos, Javier Resano, and Antonio Plaza, *Senior Member, IEEE*

IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 6, JUNE 2015

Dual-Mode FPGA Implementation of Target and Anomaly Detection Algorithms for Real-Time Hyperspectral Imaging

Bin Yang, Minhua Yang, Antonio Plaza, *Fellow, IEEE*, Lianru Gao, *Member, IEEE*, and Bing Zhang, *Senior Member, IEEE*

BSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 6, JUNE 2015

FPGA Implementation of the HySime Algorithm for the Determination of the Number of Endmembers in Hyperspectral Data

Carlos Gonzalez, Sebastian Lopez, *Senior Member, IEEE*, Daniel Mozos, and Roberto Sarmiento

J Real-Time Image Proc
DOI 10.1007/s11554-016-0650-7

ORIGINAL RESEARCH PAPER

FPGA implementation of the principal component analysis algorithm for dimensionality reduction of hyperspectral image

Daniel Fernandez[1] · Carlos Gonzalez[1] · Daniel Mozos[1] · Sebastian Lopez[2]

Received: 17 May 2016 / Accepted: 24 October 2016

4 IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 9, NO. 9, SEPTEMBER 2016

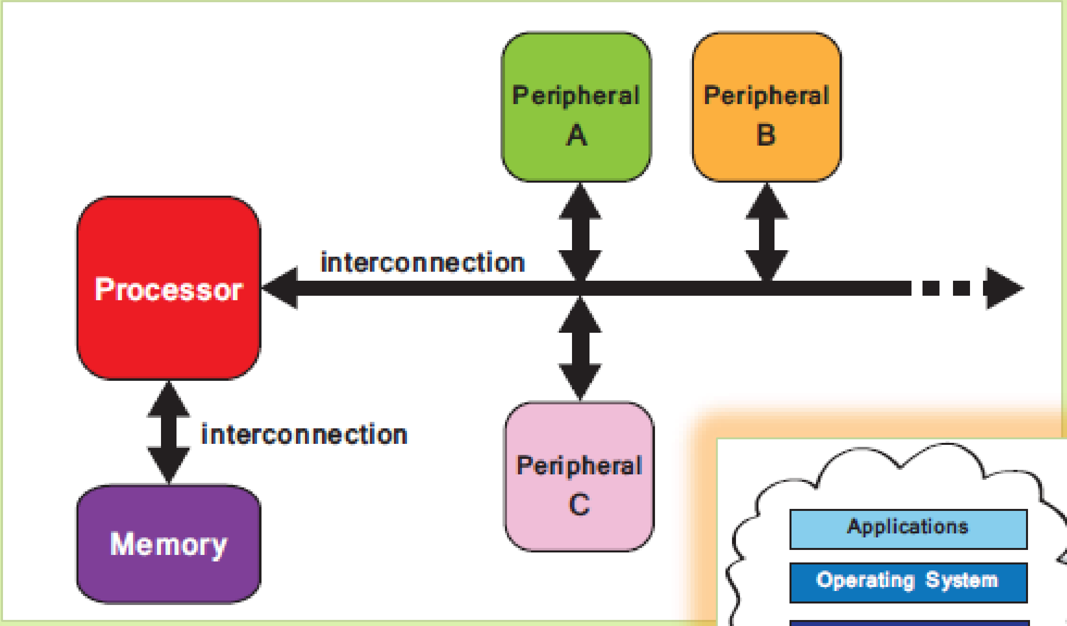
FPGA Implementation of an Algorithm for Automatically Detecting Targets in Remotely Sensed Hyperspectral Images

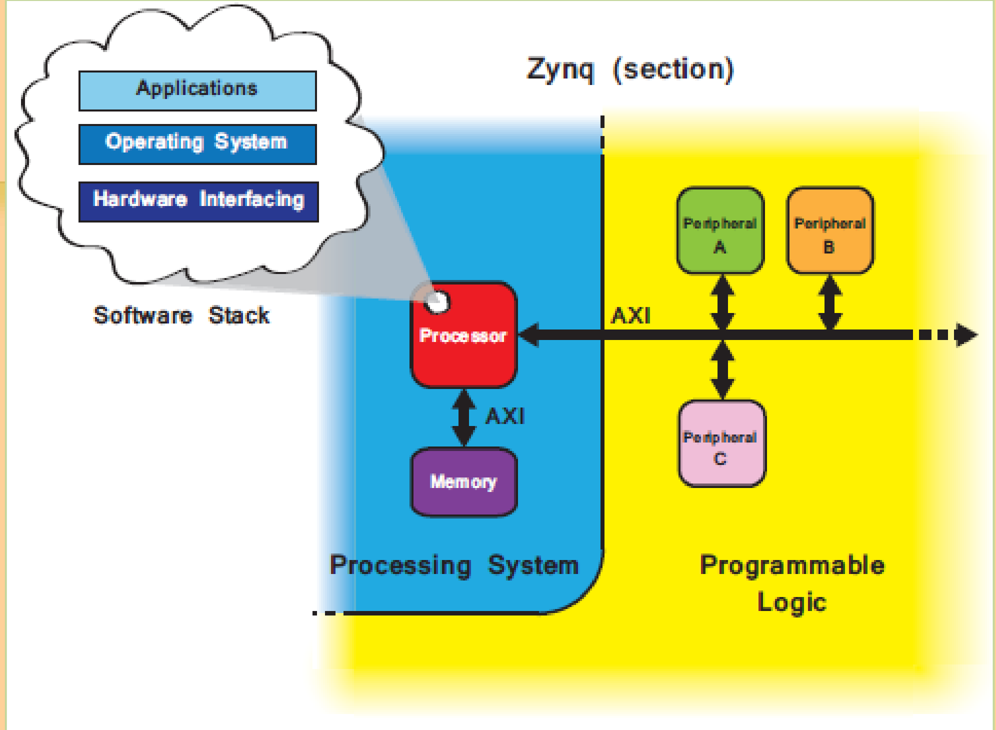
Carlos González, Sergio Bernabé, Daniel Mozos, and Antonio Plaza

***Abstract*—Timely detection of targets continues to be a relevant allenge for hyperspectral remote sensing capability. The tomatic target-generation process using an orthogonal projec- n operator (ATGP-OSP) has been widely used for this pur-**

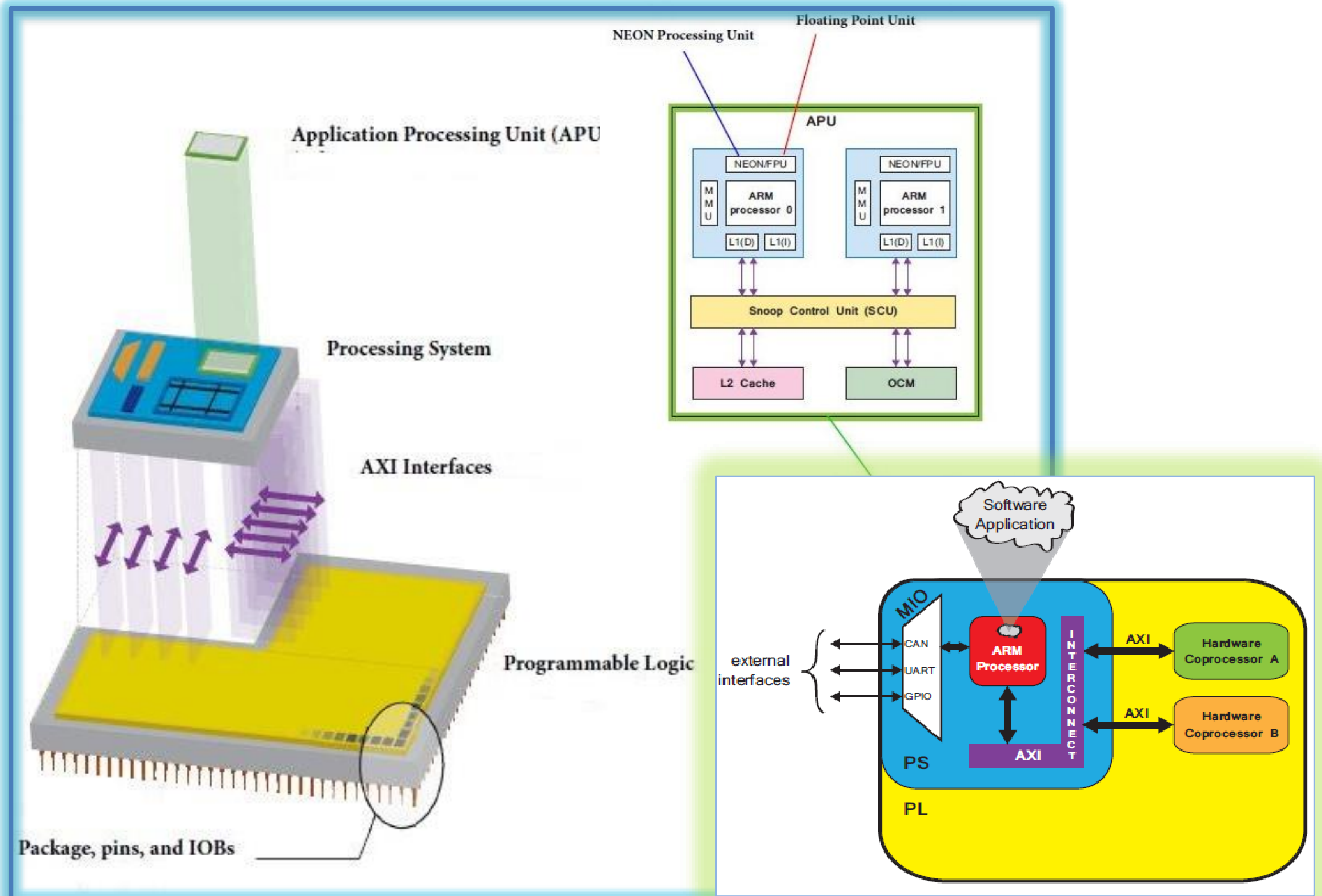
Propulsion Laboratory in California, which developed instruments such as the airborne imaging spectrometer, then called airborne visible infrared imaging spectrometer (AVIRIS) [2].

System architecture

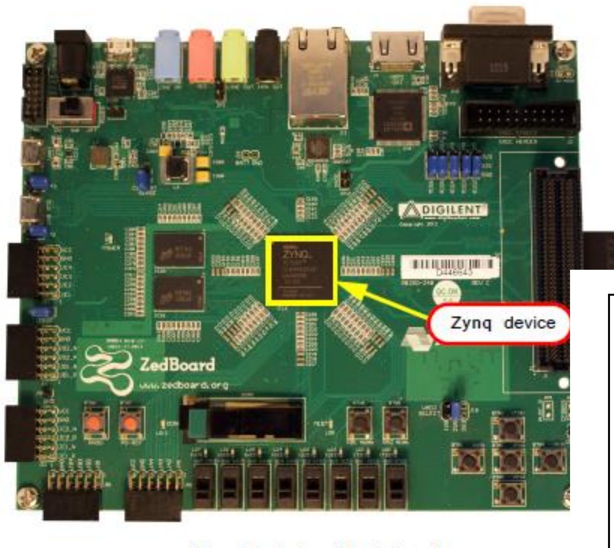


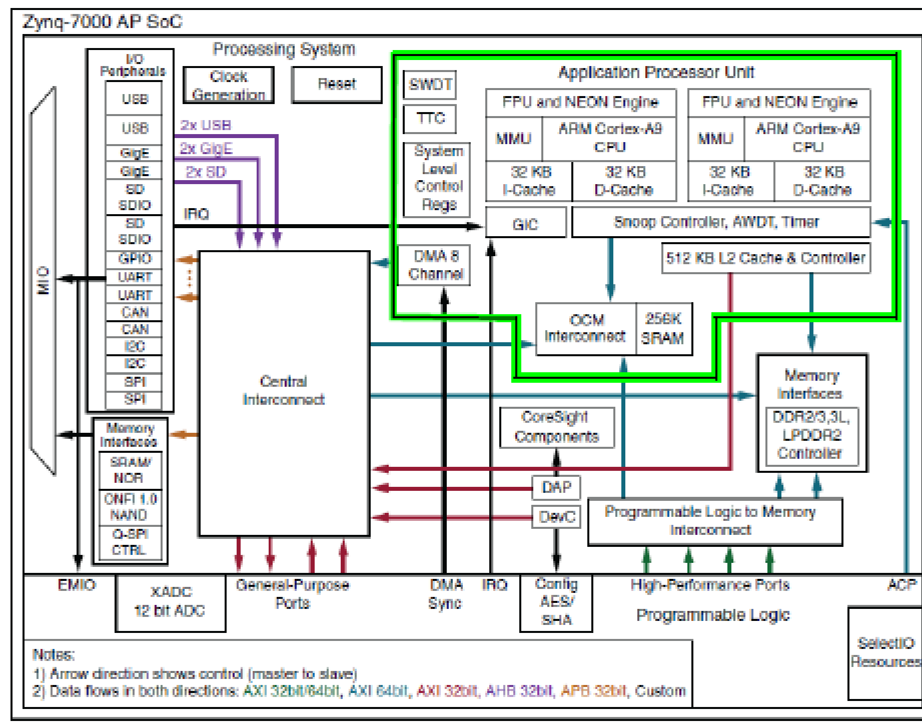


System Architecture (Zynq)

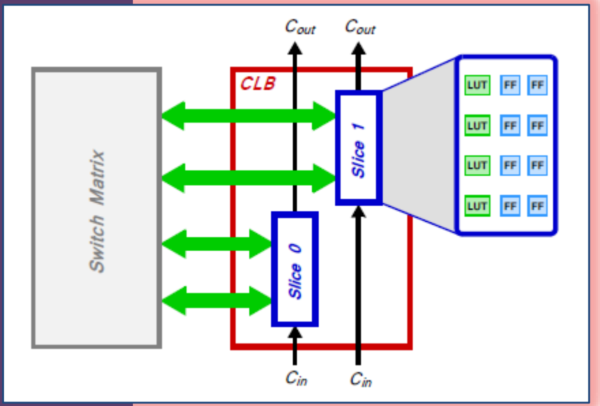


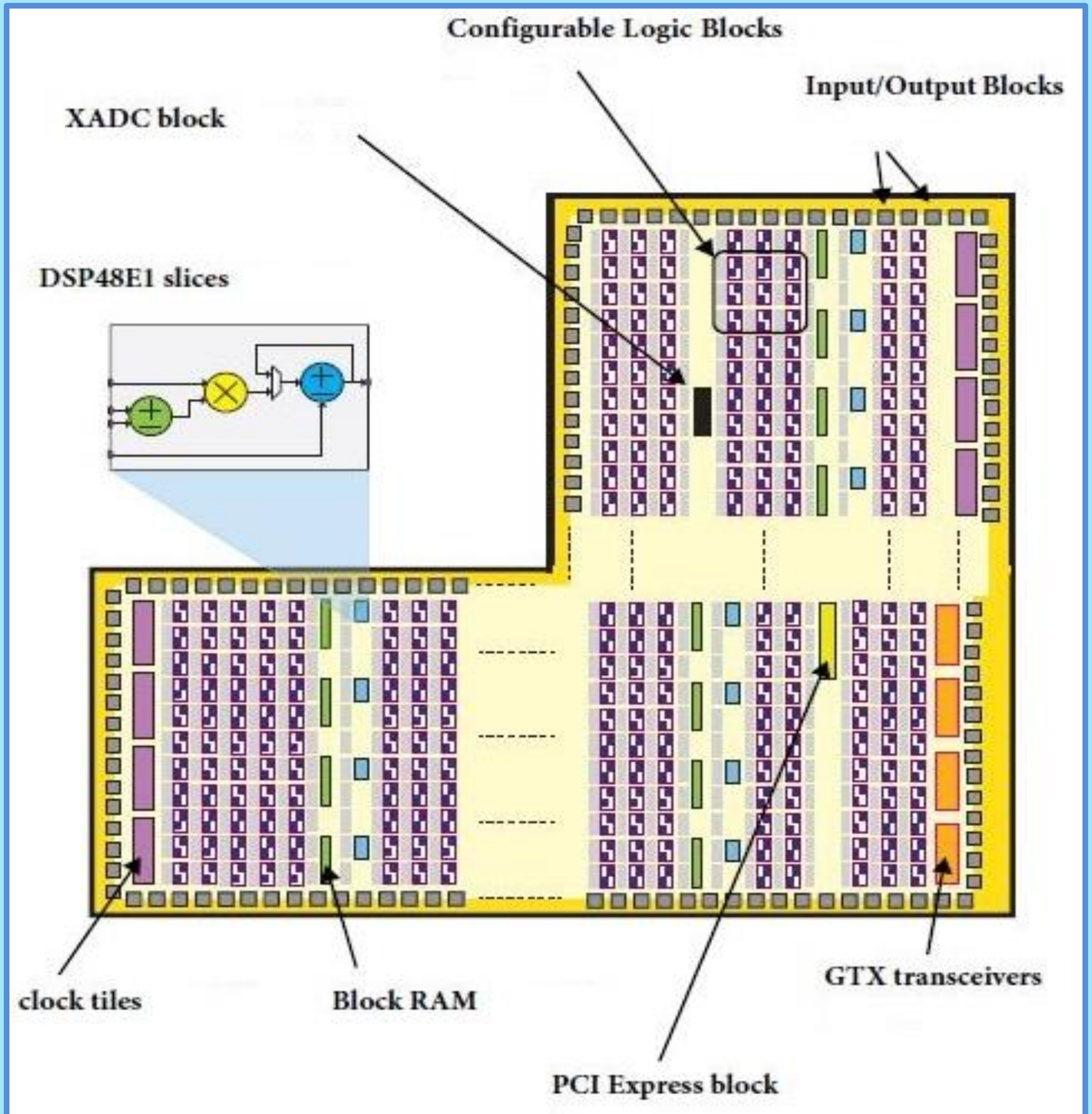
Zynq Devices





Programmable Logic





Zynq-7000 All Programmable SoC

	Device Name	Z-7007S	Z-7012S	Z-7014S	Z-7010	Z-7015	Z-7020	Z-7030	Z-7035	Z-7045	Z-7100
	Part Number	XC7Z007S	XC7Z012S	XC7Z014S	XC7Z010	XC7Z015	XC7Z020	XC7Z030	XC7Z035	XC7Z045	XC7Z100
Programmable Logic	Xilinx 7 Series Programmable Logic Equivalent	Artix®-7 FPGA	Artix-7 FPGA	Artix-7 FPGA	Artix-7 FPGA	Artix-7 FPGA	Artix-7 FPGA	Kintex®-7 FPGA	Kintex-7 FPGA	Kintex-7 FPGA	Kintex-7 FPGA
	Programmable Logic Cells	23K	55K	65K	28K	74K	85K	125K	275K	350K	444K
	Look-Up Tables (LUTs)	14,400	34,400	40,600	17,600	46,200	53,200	78,600	171,900	218,600	277,400
	Flip-Flops	28,800	68,800	81,200	35,200	92,400	106,400	157,200	343,800	437,200	554,800
	Block RAM (# 36 Kb Blocks)	1.8 Mb (50)	2.5 Mb (72)	3.8 Mb (107)	2.1 Mb (60)	3.3 Mb (95)	4.9 Mb (140)	9.3 Mb (265)	17.6 Mb (500)	19.2 Mb (545)	26.5 Mb (755)
	DSP Slices (18x25 MACCs)	66	120	170	80	160	220	400	900	900	2,020
	Peak DSP Performance (Symmetric FIR)	73 GMACs	131 GMACs	187 GMACs	100 GMACs	200 GMACs	276 GMACs	593 GMACs	1,334 GMACs	1,334 GMACs	2,622 GMACs
	PCI Express (Root Complex or Endpoint)(3)		Gen2 x4			Gen2 x4		Gen2 x4	Gen2 x8	Gen2 x8	Gen2 x8
	Analog Mixed Signal (AMS) / XADC	2x 12 bit, MSPS ADCs with up to 17 Differential Inputs									
	Security(2)	AES and SHA 256b for Boot Code and Programmable Logic Configuration, Decryption, and Authentication									

Why FPGA?

PRO:

- Compact SIZE
- LOW WEIGHT
- LOWER POWER CONSUMPTION

(Xilinx 7 series)

- RECONFIGURABILITY (PARTIAL OR FULL)
- HIGH THROUGHPUT
- REAL-TIME PROCESSING
- OPTIMIZED DATA PATHS
- RESISTS HIGH LEVEL RADIATION without changing the content of inner memories.

CONS:

LOW LEVEL HDL LANGUAGES

Deep understanding OF HARDWARE DESIGN required

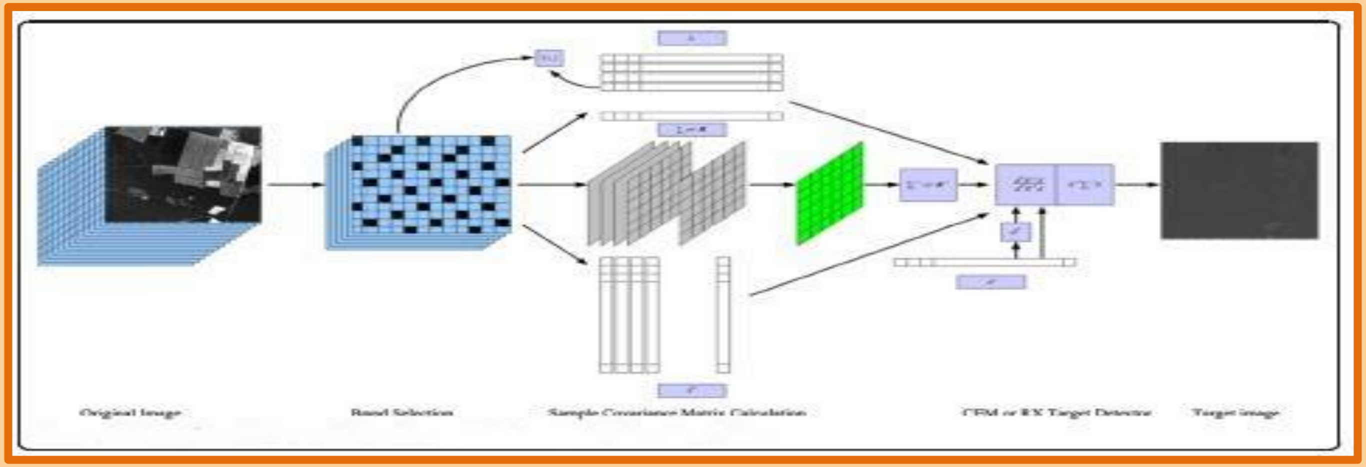
Challenges in HSI onboard system development

Algorithm Adaptation & Development

SoC Development

FPGA Implementation

System Integration



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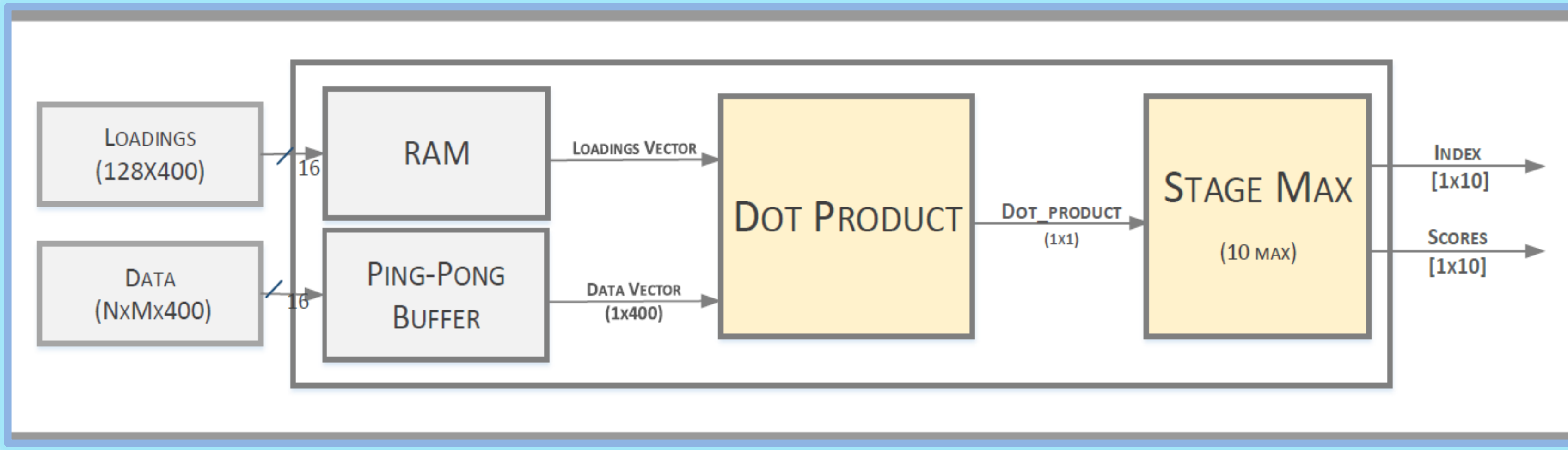
FPGA Implementation of OTFP Preprocessing Module (I/II)

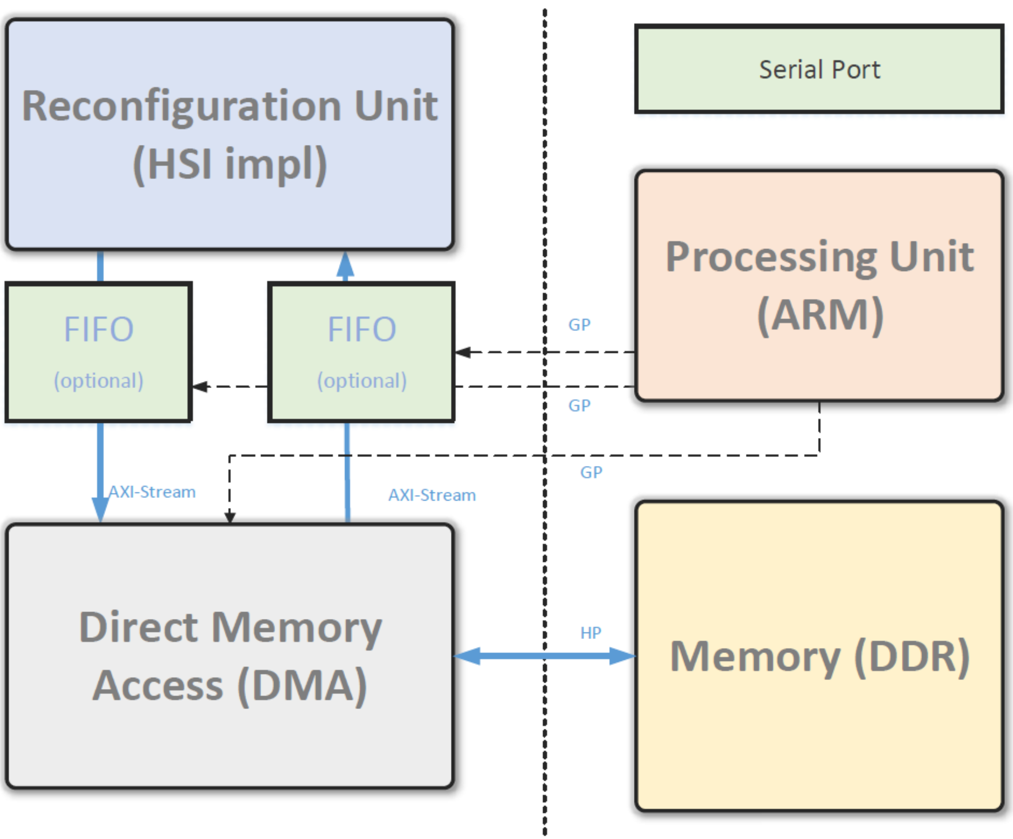
SPECIFICATION:

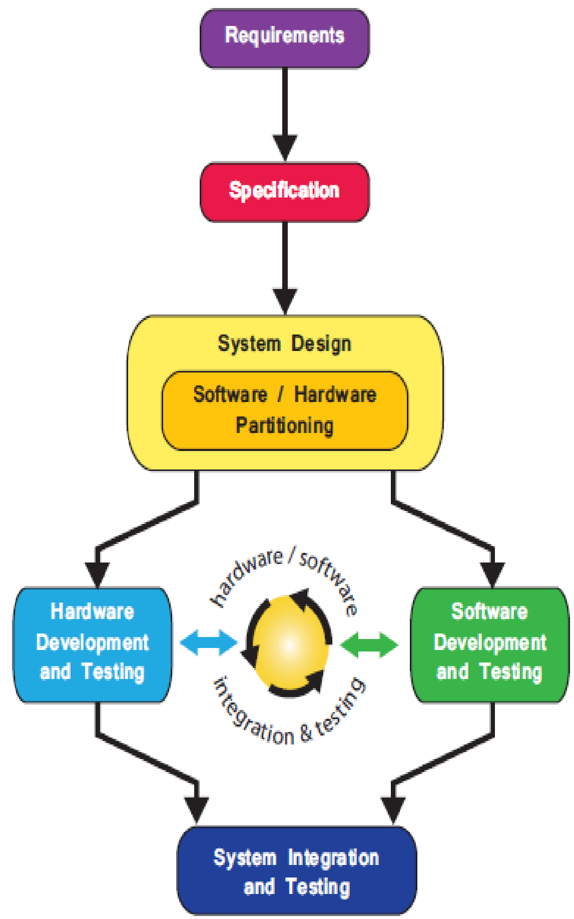
DATA CUBE- X(500x500x400)
N_load=128
Loadings_database= L(128x400)
K_max=10

Preprocessing stage:
S= ∑L_i,k* (X_i,j-X_mean[i])
Scores =max(S, k_max)



SoC Development and System Intergration for HSI application





Dynamic Partial Reconfiguration (DPR) Concept