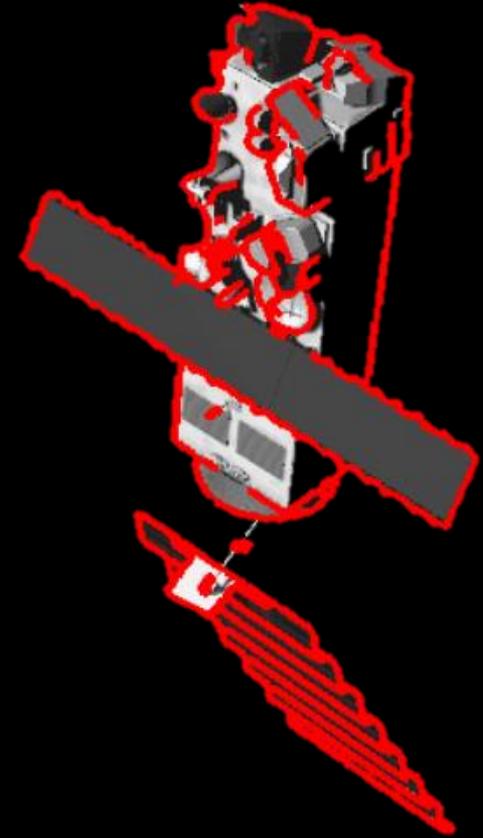


High Performance Avionics Solution for Advanced and Complex GNC Systems for ADR

HIPNOS

Clean Space Industrial Days, October 24th 2017

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George Lentaris (glentaris@microlab.ntua.gr)



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**FORTH,
GREECE**



**NTUA,
GREECE**



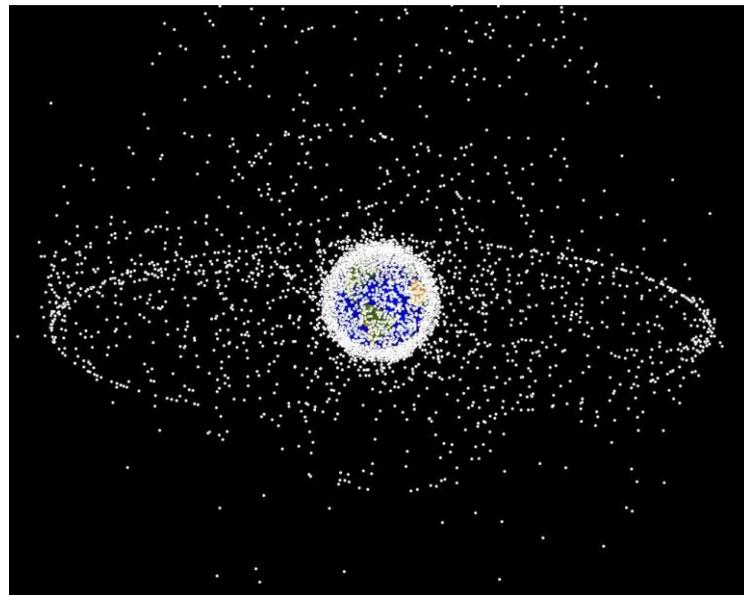
**GMV,
SPAIN**



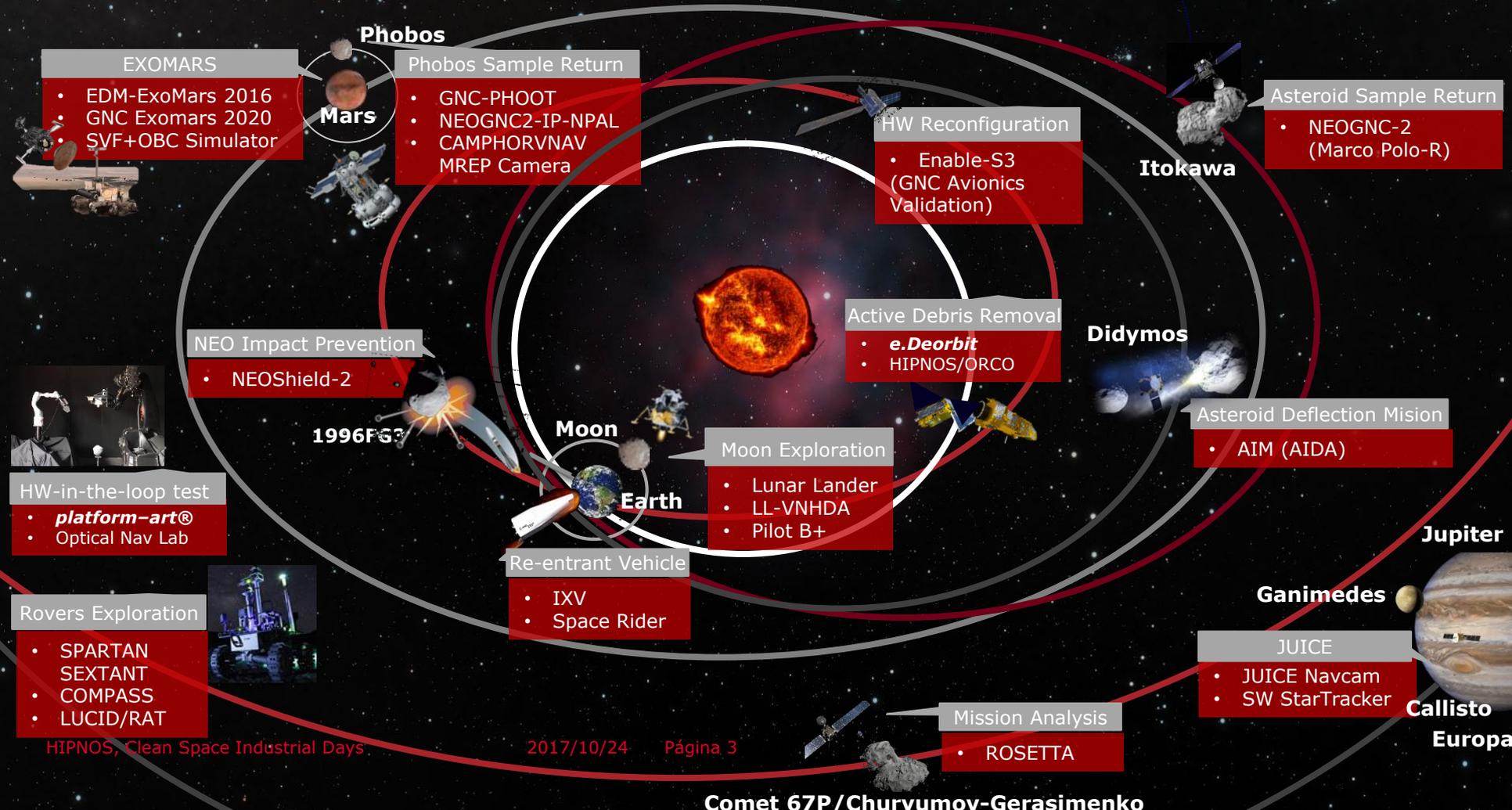
SCOPE & OBJECTIVES

Development of a representative HW/SW solution for a high-performance processing platform for Active Debris Removal missions. Implement COTS-based solution as Demonstration of the activity

- study/define the high-level architecture of a high-performance computing system for space avionics for GNC in ADR missions
- design one high-accuracy & high-complexity chain of Computer Vision algorithms to support the ADR scenario of e.Deorbit
- select the most appropriate acceleration platform in terms of speed, power, rad-hardness, mass/size, flexibility, future trends
- accelerate the CV algorithms on FPGA or GPU, or DSP, or multi-core CPU to achieve the high-speed processing required in ADR
- develop and demonstrate a preliminary, proof-of-concept system (by using COTS components and high-definition videos) with a representative ADR use-case.
- present the feasibility of implementing demanding algorithms with real-time performance on future space-grade platforms



AUTONOMOUS NAVIGATION IN SPACE



Active Space Debris Removal



ADR SCENARIO REQUIREMENTS

High-demanding on-board space applications which cannot rely on common space-grade avionics

- Large ESA owned dead satellite, uncooperative, non-passivated → e.Deorbit → ENVISAT
- RdV: assume a hold point at a distance from the target of 100m and another at 50m
 - Camera-based rendezvous until 100m
 - Forced motion approach or safe orbit approach to 50m
 - Spin synchronization
 - Approach in the target body frame to terminal hold point
 - Capture at 2m: "Capture Phase" shall assume a hold point at a distance of 2 m
- The chaser shall be able to perform relative navigation w.r.t. the target object during the full target orbit anytime of the year, fully autonomous without any ground intervention
- A camera sensor plus a relative trajectory + attitude propagation.
LED based spotlights can provide illumination for the rest of the approach.
- Trade-offs (performance, power consumption, image resolution, arithmetic precision, mass/size budget, accuracy,...)
- Consider the most representative and computationally demanding computer vision and image processing algorithms (target 10fps 1024x1024 pixel images)



Launch mass:	8,211 kg
Dimensions:	2.5 × 2.5 × 10 m
Orbit:	LEO 2°/s spin

AVIONICS PROCESSING REQUIREMENTS

Derived requirements for the processing board of HIPNOS based on e.Deorbit MSRD and relevant projects

▪ **Electrical Power**

- e.Deorbit MSRD: nothing specific (MIS-59 = mean and peak power TBD)
- similar projects: GMV-NEOGNC2-IP, GMV-CAM-PHOR-VBN
- relevant solutions with FPGA (NASA): 2-5 Watts for Zynq boards, and 5-20 Watts for multi-board SpaceCubes
- **requirement = 10 Watt (TBC)**

▪ **Mass/size**

- e.Deorbit MSRD: nothing specific (MIS-60 = mass TBD Kg)
- similar projects: GMV-NEOGNC2-IP, GMV-CAM-PHOR-VBN
- relevant solutions with FPGA (NASA): <100gr for Zynq boards, and 1.4-5.8Kg for multi-board SpaceCubes (+housing)
- relevant solutions with FPGA (NASA): 1U or 17x17x5cm for Zynq boards, 1U up to 13x18x23cm for V5QV (+housing)
- **requirement = 0.5 Kg (TBC)**
- **requirement = 20x20x10 cm³ (TBC)**

▪ **Processing power (projected to CPU)**

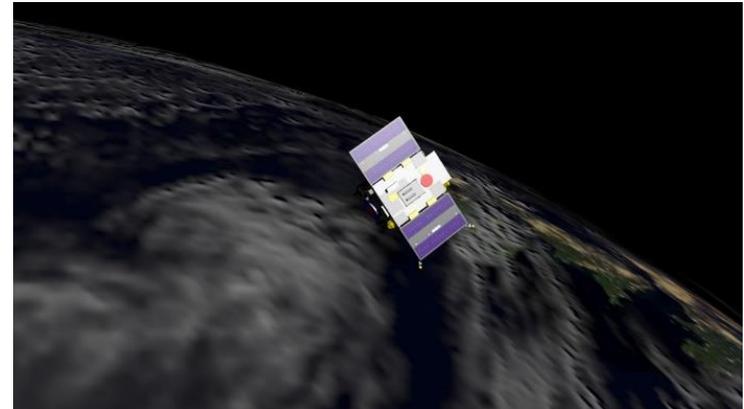
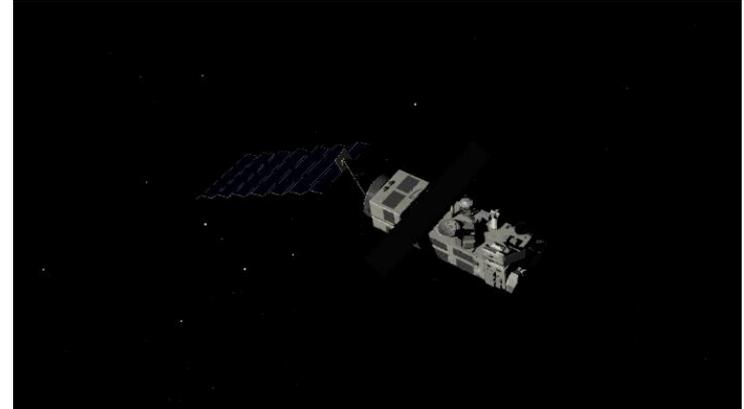
- e.Deorbit MSRD: nothing specific
- similar projects: extrapolated IP results from [SEXTANT] for high-rate high-definition images show 100x more power
- **requirement = 15.000 MIPS (TBC)**

▪ **Interfaces**

- e.Deorbit MSRD: nothing specific
- **requirement = sensors-board : space-qualified link for 2Mpixel image at 10fps (TBC)**
- **requirement = OBC-board : TBD high-speed bus (data/image) + TBD low-rate bus (control)**

ADR SCENARIO DEMONSTRATION

- ENVISAT AND PROBA-2
- ENVISAT sequences were generated using ASTOS camera simulator
- Two trajectories for ENVISAT:
 - Observation phase: chaser stands about 50m from target
 - Approaching phase: From 30m down to 10m
- PROBA-2 sequences were generated using commercial rendering SW including the Earth in background
- 1 trajectory for PROBA-2
 - Spin Synchronization maneuvers: Chaser synchronizes rotation with target
 - Later approaches to the target



TRADE-OFF AVIONICS

- STATE-OF-THE-ART

- SPACE-GRADE
- COTS

GR712RC Dual-Core SOC Leon3-FT	Space-Qualified	100 MHz	140-200 DMIPS	3-6 Watts
RAD750 PowerPC	Space-Qualified	200 MHz	400 DMIPS	15-20 Watts
Intel Core i5-2500K 4-core (2011)	COTS	3,300 MHz	83,000 DMIPS	73-100 Watts

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P4080 Octo-core board	Latch-up Immune Virtex-5 Voting System	1,500 MHz	27,600 DMIPS	>45 Watts



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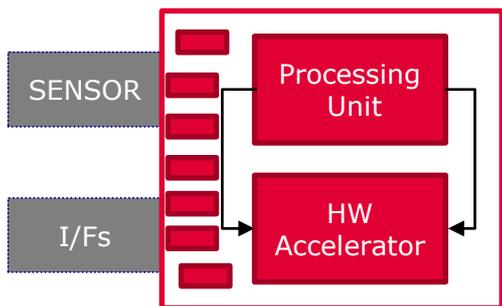
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- COTS

- FIRST GENERAL ITERATION:

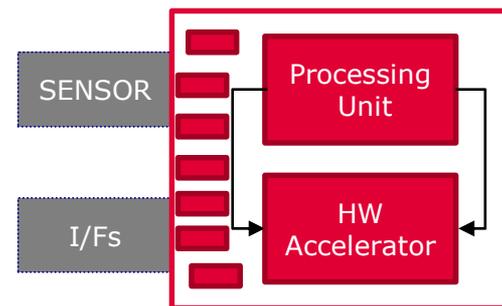
- CONVENTIONAL SPACE-GRADE PROCESSORS
- SPACE-GRADE SRAM-BASED FPGAs
- DSPS
- GPUS
- MULTICORE-MULTIPROCESSOR
- SYSTEM-ON-CHIP

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Doc. Code



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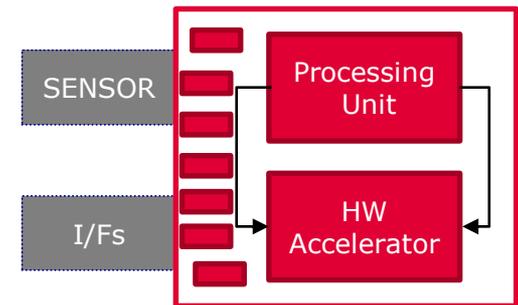
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TCLS ARM4SPACE	DAHLIA quad-core ARM cortex-R52	MPSoc Multicore ARM + FPGA logic Zynq UltraScale+	ARM Cortex M0+ COTS ARM Cortex-A Snapdragon 820	LEON-5
HPDP manycore	MPPB/SSDP multi-dsp board	RC64 CEVA DSP manycore 500x faster GR712	TI SMV320C6727B C67x + VLIW DSP	ARM (4-core) + TMS320C66x (8-core C66x DSP)
Virtex5-QV	RTG4	RTAX, ProAsic3, CTOS SmartFusion	BRAVE: NG-MEDIUM NG-LARGE (+ARM) NG-ULTRA (+ARM)	Zynq7000 SoC Zynq UltraScale+
Myriad Movidius	LPGPU rad-tolerant	NVIDIA GPU	SYSTEM ON CHIP	



BENCHMARKING

- done extensive testing/evaluation
 - with both in-house & literature work
 - for all processor categories
 - for computer vision tasks
 - focused mainly (but not only) on **performance** and **Watt**
- **in total, more than 30 platforms and 10 benchmarks**

	In-house development & testing	Literature survey	
platforms	FPGA	Xilinx Virtex6 VLX240T-2, Zynq7000 (Z7020, Z7045)	Altera Stratix III E260, Xilinx Virtex 5QV, Virtex4 VLX100, Virtex6 VSX475T, Zynq7000
	CPU	desktop Intel i5-4590, laptop i3-4010U embedded: ARM CortexA9, Intel X1000 space: LEON3, OCE E698PM (LEON4)	desktop: Intel i7-3820, AMD FX-8120 embedded ARM CortexA15 space-grade BAE RAD5545
	GPU	Nvidia GeForce GTX 670, GTX 680, GTX 960	Nvidia GTX 980Ti / 650Ti / 295, Tesla C2050, mobile: Nvidia Tegra K1/X1, ARM Mali-T760
	DSP	space-grade Xentium MPPB embedded multi-core Myriad2	TI multi-core TMS320C6678 and 66AK2H14, 1-core C674x, 64-core RH RC64 (MACSPACE)
benchmarks	2D convolutions (5x5 to 11x11), Harris-corner & Canny-edge detectors, Stereo Matching, Hyperspectral search, Pose Estimation (incl. feature detection, description, matching), Super-Resolution	2D convolutions and SAD (up to 25x25), Harris-corner & Canny-edge detectors, Stereo Matching, Image Denoising and Block Matching, Hyperspectral imaging, <i>etc.</i> (plus nominal DMIPS and MFLOPS figures)	

- clouds of results, vary per platform & benchmark (peculiarities of computational model, chip node/size, etc.)
- challenge tackled methodically, comparison converged in big consistent picture

COMPARISONS

1st ITERATION (BIG PICTURE)

- CPUs worst performance/Watt
- FPGAs best perf/Watt (10x)
- FPGA vs desktop-GPU, not far w.r.t. speed, but w.r.t. power..
- mobile-GPU vs desk-GPU, trade 10x performance for Watt
- mob-GPU vs many-DSP, similar performance and power

	rad-hard CPU (1-core)	embedded CPU (1-core)	desktop CPU (1-core)	mobile GPU	high-end DSP	FPGA	desktop GPU
Throughput	0.2–1.7	0.5–2	20–100	50–150	50–240	300–1460	200–2000
Power (W)	1–18	1–2	20–90	6–10	1–10	2–10	70–195
Perf/Watt	0.1–0.6	0.25–2	0.5–1	8–15	12–50	60–250	5–25

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2nd ITERATION (BEST 28nm COTS)

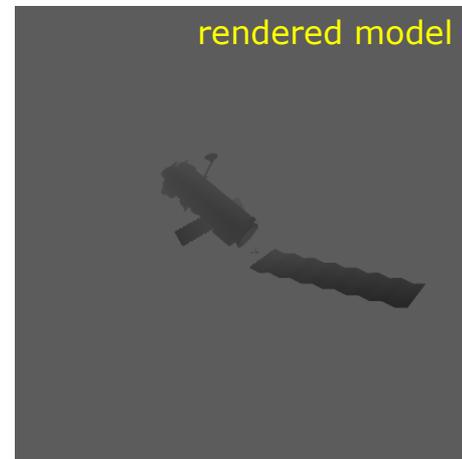
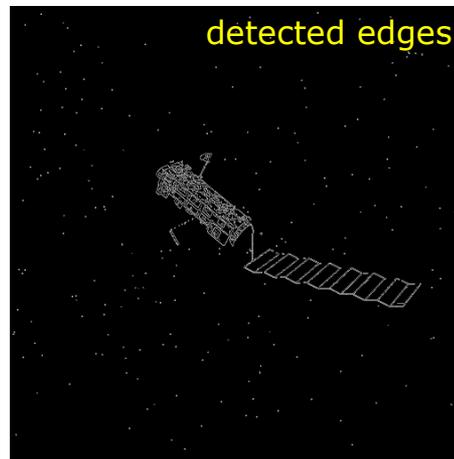
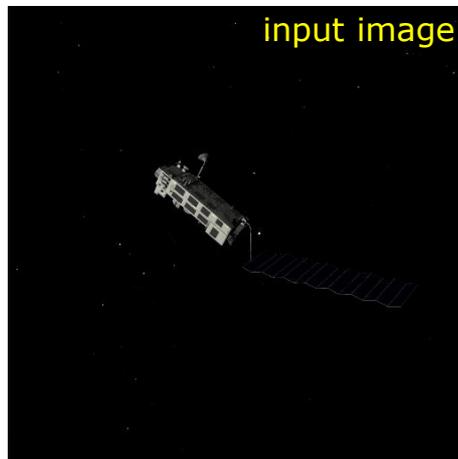
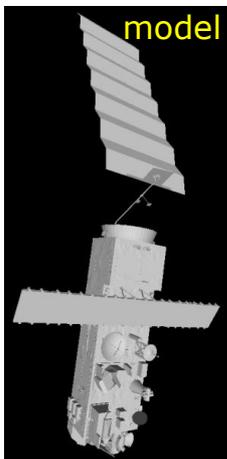
- SoC are most useful for acceleration
- DSPs are closing in (vs FPGA), but
 - Zynq 10x perf vs Myriad2 for HD
 - Zynq 10x perf/W vs TI-C66x
- Myriad2 lowest power (1W)
- Zynq highest speed (with slow clk)

	4-core LEON4 (E698PM) 600 MHz	12-core VLIW (Myriad2) 600 MHz	8-core DSP (66AK2H14) 1200 MHz	FPGA (Zynq7045) 200–300 MHz	desktop GPU (GTX 670/680/960) ≥ 1 GHz
Performance	< 20	50	70–240	430–1460	600–1800
Power (W)	≈ 2.8	1	≈ 10	4–6	> 70
Perf/Watt	< 7	50	7 – 24	110–240	< 25

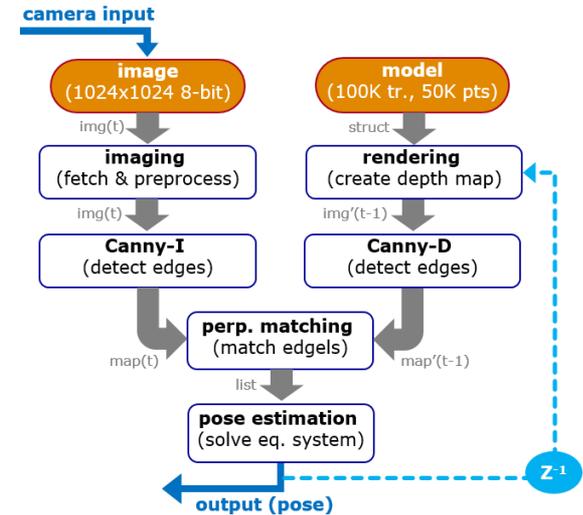
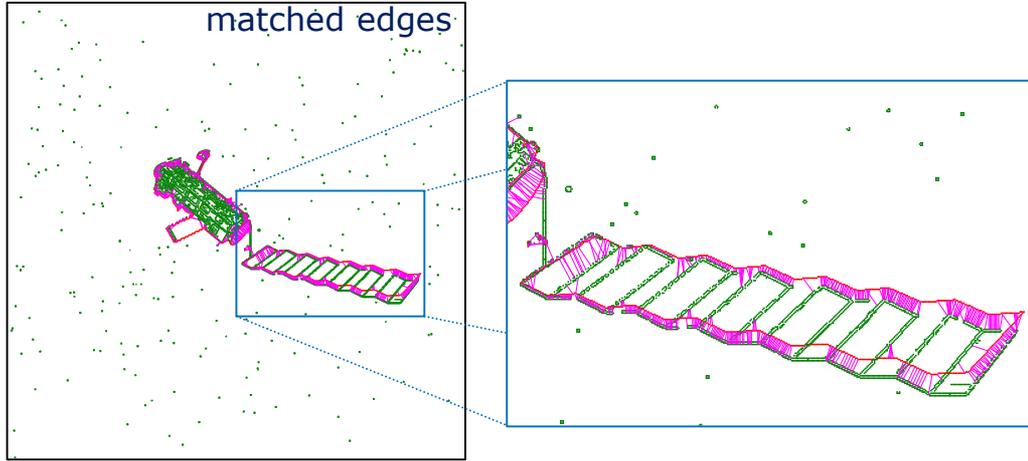
➤ **selected:** Zynq7000 on MMP board (6x10cm² 65gr), also due to connectivity & rad mitigation opportunities

POSE ESTIMATION 1/2

- **Developed** a model-based, monocular 3D tracking algorithm based on edges (edges are robust to noise and illumination changes; can be accurately and rapidly localized in images)
- Inputs object mesh model (+ approximate initial 3D pose) and the sequence of images
- **Algorithm:**
 1. Intensity **edges are detected** on the input image (with Canny)
 2. The **model is rendered** (i.e. projected) with the approximate 3D pose (of the previous state); visible depth **edges are also detected** in the projection (rendered model)



POSE ESTIMATION 2/2



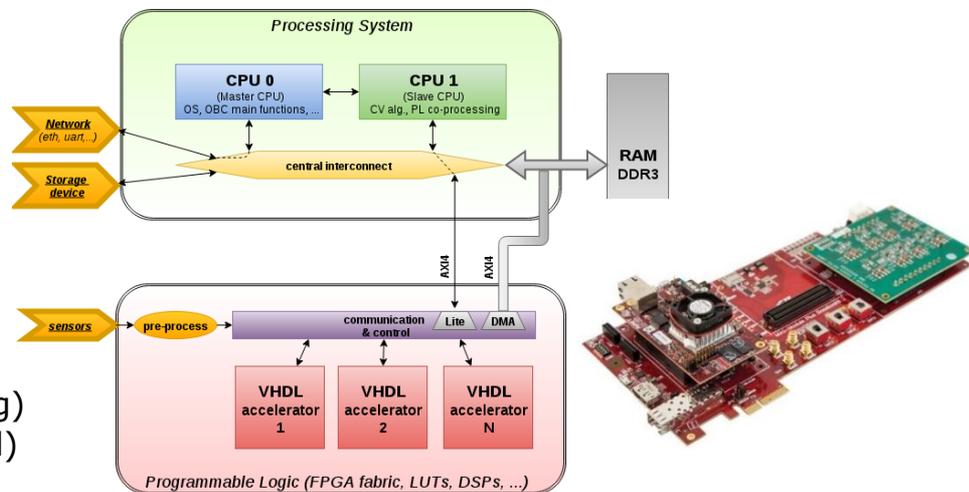
• Algorithm (cont'd):

3. Depth edges are matched with intensity edges, searching in directions perpendicular to the depth edges
 4. Perpendicular matches are used for estimating the incremental (i.e., frame to frame) pose; outliers are filtered out in a two-level robust regression framework (LMedS + M-estimation)
- ❖ Incremental pose is integrated with the approximate pose (previous state) to yield a new pose estimate (current state) and the process repeats with a new frame

DESIGN OVERVIEW

PLATFORM

- System-on-Chip Zynq (MMP module + baseboard)
 - 2x CPU : one dedicated to the CV task
 - FPGA : to accelerate selected CV functions
 - comm. : over AXI4, with DMA for ~3Gbps
- deploy Ubuntu OS with Xillybus (for fast prototyping)
- *sdcard* for pre-stored images (imaging not analyzed)



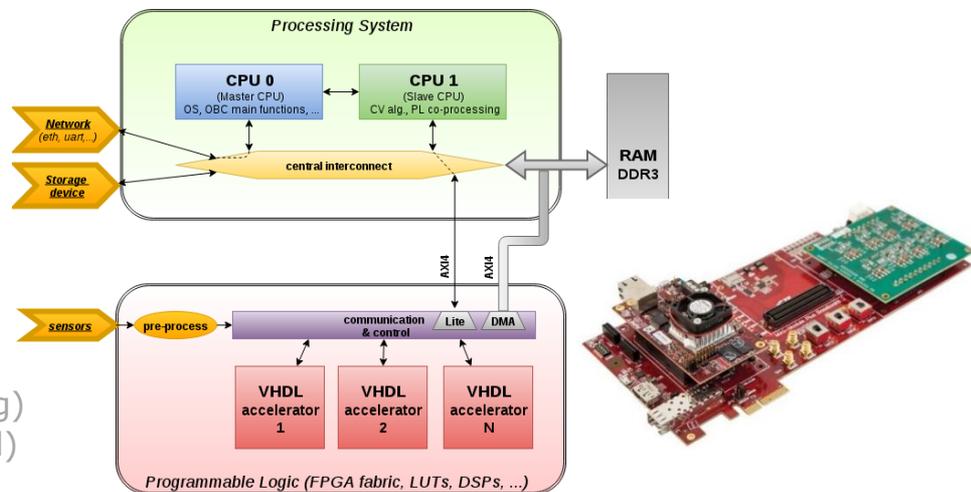
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PROFILING

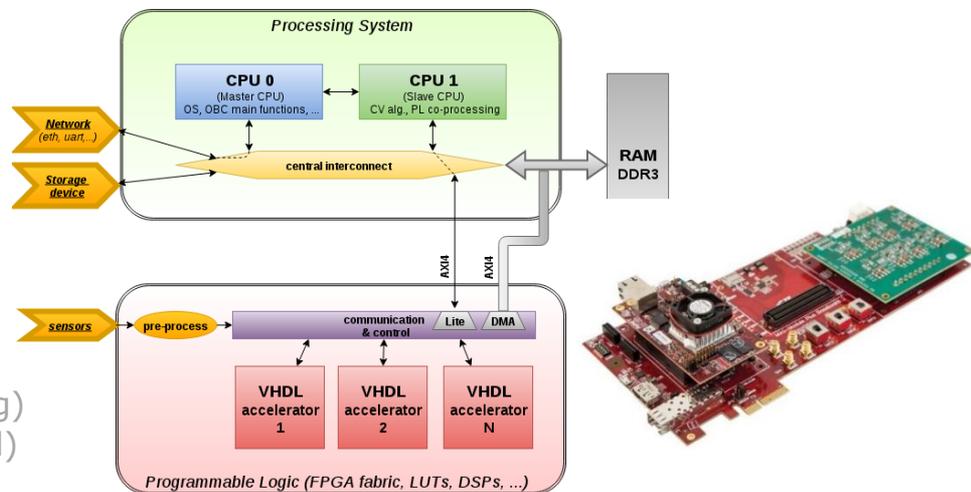
- on ARM Cortex-A9 @ 667MHZ (C/C++, single-threaded)
 - time/frame = 1–1.8 sec (~ 1/2 FPS, depends on distance)
 - 90% for pixel-based processing (Rendering, Canny)
- for few functions, achieved ~3x via NEON SIMD, but goal=10–50x



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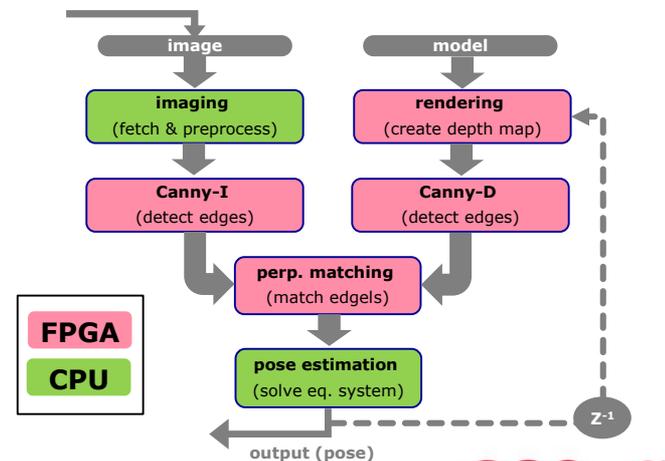


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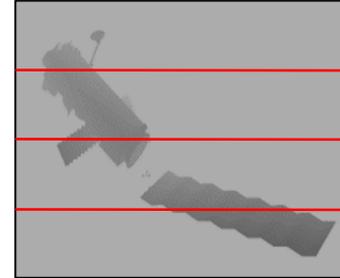
HW/SW PARTITIONING

- base on methodology, consider multiple requirements per function (time, memory, arithmetic, SW complexity, communication,...)
- roughly: pixel/edge processing on FPGA, algebra equations on CPU
- 94–97% of computation accelerated on FPGA



HW ARCHITECTURE, VHDL

- parameter tuning and customization to given problem
 - tests to fix edge thresholds, number of control points, word-lengths, etc...
 - analysis to transform floating- to fixed-point arithmetic (used a mix of both)
- memory optimizations
 - render image in 4 bands (reuse RAMBs), sliding windows
 - process data on-the-fly, avoid on-chip buffering



RESULTS

RESOURCES

- tested on biggest Zynq7000 FPGA (xc7z100-2 of MMP)
 - 36% LUTs, 48% DSPs, 77% RAMBs, $F_{max} > 200\text{MHz}$
 - most demanding is Renderer (94% logic of design)
 - power $\approx 4.5\text{W}$ (peak 9W) (CPU@667MHz, PS@200MHz)
- rough estimations for other FPGA devices
 - xc7z045/xc7z030 (smaller): maybe feasible, requires much optimization, tolerable penalty in time/accuracy
 - zu19eg (big upcoming RT): easy fit, utilization $< 30\%$
 - ng-large (EUR): $\sim 20\%$ more challenging than xc7z030

	LUT*	DFF	DSP	RAMB36
<i>Canny**</i>	2948	3174	4	346,5
<i>Matching</i>	298	389	-	5,5
<i>Renderer**</i>	93383	148071	966	224
<i>Xillybus+Misc</i>	2895	3777	-	6
TOTAL	99524 (36%)	155411 (28%)	970 (48%)	582 (77%)

*Zynq xc7z100-2L (277K LUTs, 554K DFFs, 2020 DSPs, 755 RAMB36)

**Image 1024x1024 16-bit (Canny: 2 maps) (Renderer: 4 stripes)

IMPLEMENTATION RESULTS

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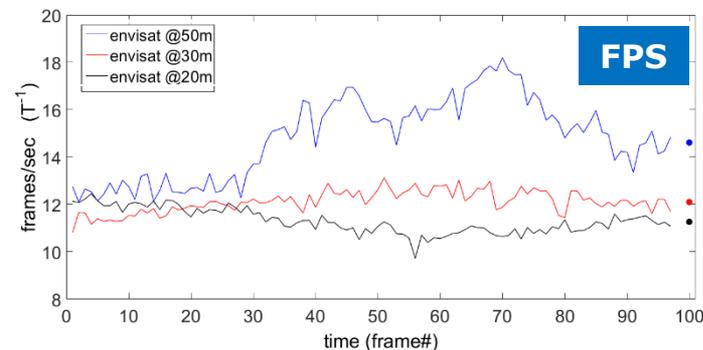
SPEED

- Time per HW kernel = 5–11ms (plus 55ms for SW function)
- Acceleration (vs ARM) = 19x (system, up to 62x for kernels)
- FPS = 12 on avg. (10–16 depending on ENVISAT distance)

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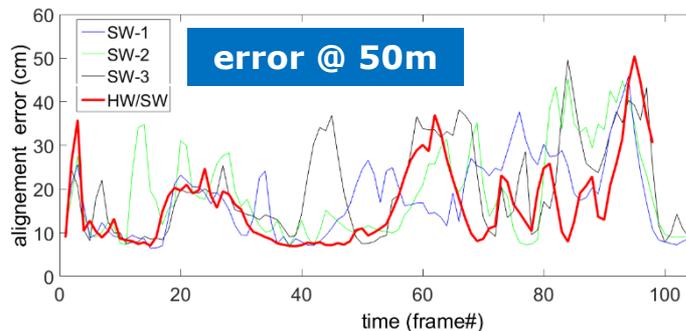
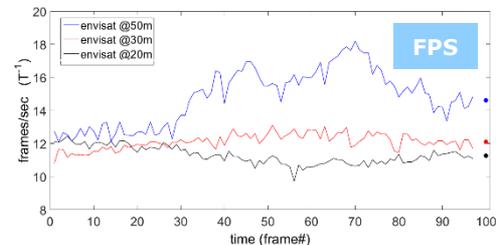
ACCURACY

- analyzed for 100's frames at 50m, 30m, and 20m
- in general, alignment error $< 1\%$ (as good as in SW)
- few bad cases (7%, lost track), corrected in new alg.

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CONCLUSIONS

FROM TRADE-OFF STUDY

- latest space-grade CPUs 10x faster than predecessors, still slow for high-performance VBN (e.g., 0.1x)
- by offering best perf/Watt vs all platforms, FPGAs can bridge the gap with reasonable power budget (<10W)

FROM ALGORITHM DESIGN

- edges are good/sufficient as features for ENVISAT
- rendering allows any 3D model to be used (without preprocessing/assumptions)

FROM SYSTEM DEVELOPEMNT

- Xilinx Zynq on MMP achieves (specifically for pose estimation in ADR with passive sensors/cameras)
 - 10+ FPS for 1024x1024 images (or 5+ for 2048x2048)
 - power around 5W (peak 9W)
 - error around 1%, most often less than that



THANK YOU questions?

Publications:

- Lentaris, George, et al. "Project HIPNOS: Case study of high performance avionics for active debris removal in space." VLSI (ISVLSI), 2017 IEEE Computer Society Annual Symposium on. IEEE, 2017.
- Lourakis, Manolis, et al. "Model-based Visual Tracking of Orbiting Satellites Using Edges", Proc. IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS), 2017.
- Lentaris, George, et al. "High Performance Embedded Computing in Space: Evaluation of Platforms for Vision-based Navigation", AIAA Journal of Aerospace Information Systems, under minor revision, 2017.

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