GNSS-AI on-EDGE – Onboard detection of GNSS signal disturbances by DNN (ESA contract no. 4000135301)

Executive Sumary Report

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1 Introduction

Location based services (LBS) are in increase with high demand for better and better location accuracy. Not only mobile applications addressing mainly consumer mass market (location-based advertising, augmented reality) but also more professional or safety related solutions will benefit or arise, being able to use precise navigation (GNSS-enabled 112 emergency call, mapping, workforce management, asset management, …). One of major stakeholders, supporting innovative research fields, is also the European GNSS Agency (GSA) and its GNSS Raw Measurements Task Force, launched in 2017 [RD63]. Needs for better navigation precision are underpinned also through GNSS market trends and outcomes. The global GNSS downstream market revenues from both devices and services are anticipated to grow from €150 billion in 2019 to €325 billion in 2029 with a CAGR of 8%. Current COVID19 situation further exposes a potential demand for precise navigation and warns about how important is further research and development in GNSS section.

On the other hand, in recent years AI technology has been advancing in the segment of deep learning techniques opening new application areas also in Space segment; navigation and control are one among them. AI technologies could provide highly added value in topics concerning ionosphere monitoring and modelling, radio frequency interference modelling or clock anomaly modelling. A severe ionospheric storm already occurred in the past, producing an increase in the electron density which led to large ionospheric refraction values on the GNSS signals. These ionospheric conditions were beyond the capability of the GNSS ionospheric model and therefore producing large positioning errors for single-frequency users. Beside scintillation effects and other unexpected events such as GNSS satellites onboard failures or degraded performance, GNSS receivers' failures could cause unexpected loss of precision without notification resulting in serious impacts on the above-mentioned services. It could take tens of minutes before the anomaly is detected and reported by GNSS operators which could be too late in time critical situations. Issues where system IO dependency is nonlinear can be very well addressed by AI technology.

SkyLabs company done an alternative approach to well established techniques for detection of navigation precision loss by machine learning techniques based around deep neural networks (DNN). During recent years DNNs have shown a great potential in performing difficult AI tasks including computer vision and robotics. While DNNs deliver state-of-the-art accuracy on many AI tasks, it comes at the cost of high computational complexity. To address new market trends SkyLabs solution is based on local inference engine (AI@Edge) with optimized DNNs to enable low cost, power efficient and real time performance. The HPC-AI is a high-performance microcontroller in a single-board computer, designed for LEO applications. HPC-AI provides a versatile design in terms of variety of resources, extension possibilities and available interfaces.

Figure 1: HPC-AI

The HPC-AI itself can be used as a single board computer, or in dual or even multiple redundant configurations. The HPC-AI integrates SM, which is supervising operation, gathers critical housekeeping data and performs a reconfiguration, in case of a serious anomaly. The HPC-AI is highly reconfigurable module, with possibility to store different functions, with respect to SW images. HPC-AI enables also reconfiguration of the function during flight or even uploading new SW or patches of the nominal on-board software. The HPC-AI is powered by the PolarFire SoC RISC-V processor cluster, with 2GB of LPDDR4 memory (ECC protected) and 2 GB NVM Flash storage, in 1GB redundancy configuration (EDAC protected), and user available space is 512MB (table 1). NVM storage for TM data, logs, etc. one bank of MRAM is foreseen, in total of 128kB (EDAC supported) user available space.

Table 1: HPC-AI BBM - Technical specification

	Description	Comment
Processor	PolarFire SoC RISC-V 64-bit processor	
On board memories		
Data memory	LPDDR4 2 GB (512 Mb x 32-bit)	EDAC protected
TM storage	Serial MRAM 4 Mb (unlimited read/write endurance, SEE immune)	EDAC protected
Mass storage	2 GB	High speed hot redundant NAND Flash (EDAC protected)
On-board Communication interfaces	Redundant CAN bus Redundant High speed LVDS Redundant 1000 Mbps Ethernet PCIe gen 2 x4	
Supply voltage	5 V DC (+/- 10%)	
Power consumption	TBD	
Dimensions:	95 x 91 x 11 mm	
Operation temperature	-10ºC to +60ºC	
Storage temperature	-20°C to +65°C	
Mass:	56 g	

HPC-AI includes extension interface (USB/PCI-e) to support different AI@Edge inference processors. During project execution Movidius inference processor was used (figure 2).

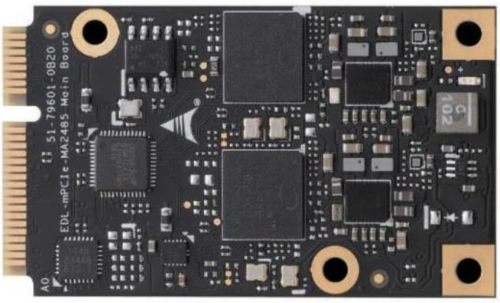

Figure 2: Movidius w MyriadXVPU

Movidius hosts the Myriad X Visual Processing Unit which is special purpose-built vector processor for the whole computer vision pipeline. The Myriad X has 2.5 MB of centralized shared on-chip Memory. The memory architecture should allow up to 400 GB/sec of internal bandwidth, minimizing latency and reducing energy consumption by minimizing off-chip data transfer. The VPU can reach 4 TOPs in total and 1 TOP of deep neural network inference but can only handle FP16 operations or lower precision.

Two separate DNN models were developed, the first one detecting scintillation effects presence in GNSS signal and the second one detecting start of spoofing event. Each of models run on its own edge processor. For evaluation purposes inference results were transmitted to PC and presented through GUI Monitor application (figure 3). The Monitor program displays real-time data for the prediction of spoofing and scintillation for each channel. Left graph at the bottom of the GUI window shows the number of spoofed channels and valid channels and the right graph shows ratio of spoofed channels compared to valid channels. Both DNN models for scintillation detection in Tensorflow format inferred on PC and OpenVINO format inferred on Movidius were evaluated with no differences noted as seen on table 2. Also, DNN models for start of spoofing detection showed no differences. For spoofing detection, we were able to achieve a performance of 168 iterations per second, which translates to around 6 milliseconds per iteration. As for scintillation, we were able to process 418 samples per second, which is equivalent to 2.39 milliseconds per iteration. Results demonstrate the real-time capabilities of our solution (current version of DNNS and inference processors), with both processes able to operate quickly enough to detect scintillation and spoofing in live GNSS signals.

Table 2: Scintillation detection results comparison

	Precision	Recall	F-score
PC	0.8	0.9	0.853
Movidius	0.8	0.9	0.853

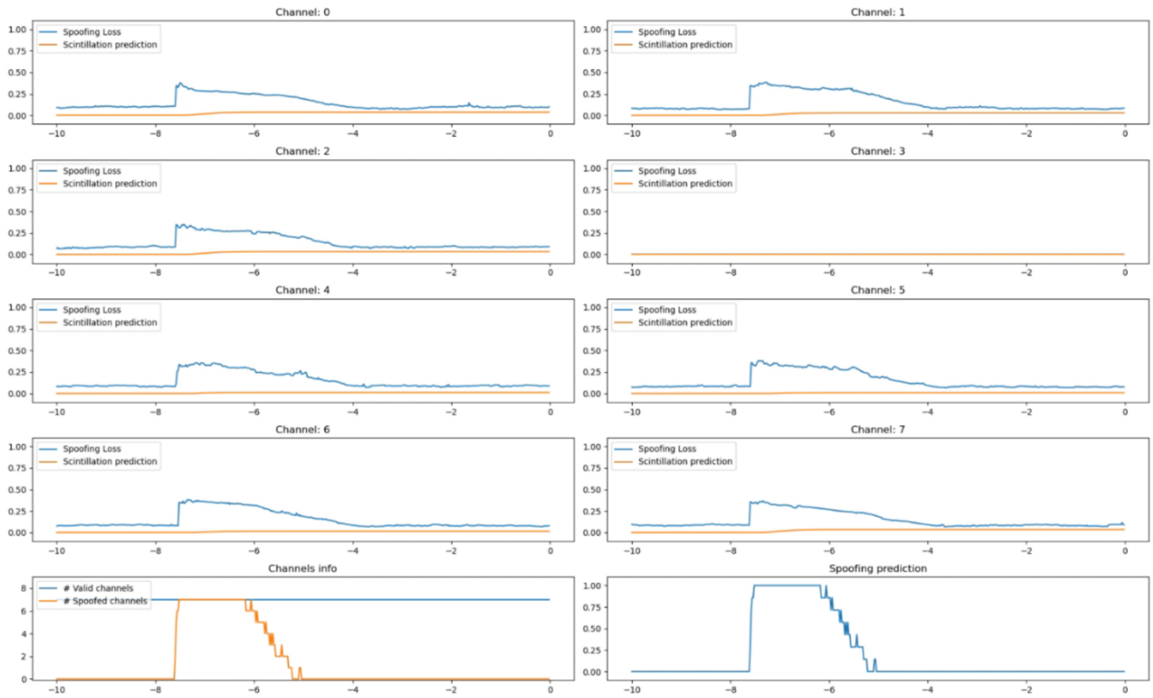

Figure 1: GUI Monitor

Table 3: Real-time performance

	Sample size [ms]	AI-HPC (Movidius) inference time per sample [ms]	Realtime factor [xRT]
Scintillation	20	5.95	3.3
Spoofing		2.39	8.3