# FUNCTIONAL SAFETY AND THE GPU

Richard Bramley, 5/11/2017



## AGENDA

How good is good enough

What is functional safety

Functional safety and the GPU

Safety support in Nvidia GPU

Conclusions

## HOW GOOD IS GOOD ENOUGH ?

# ACCIDENT STATISTICS- US<sub>1</sub>

Description	2013 Statistics	2015 Statistics				
Fatal Crashes	30,057	35,092				
Non-Fatal Crashes	5,657,000	6,263,834				
Number of Registered Vehicles	269,294,000	281,312,446				
Licensed Drivers	212,160,000	218,084,465				
Vehicle Miles Travelled	2,988,000,000,000	3,095,373,000,000				
Fatal Crash Rate in FITs 2,3	250 - 500	283 - 566				
Non-Fatal Crash Rate in FITs 2,3	46K - 92K	51K - 102K				
What is an appropriate target ?						

#### **Google** Non-Fatal Crash FIT Rate = 150K

<sup>1</sup>Source: Traffic Safety Facts 2013/2015, NHTSA document reference DOT HS 812384 <sup>2</sup> Derived from NHTSA data on driver related fatal crashes <sup>3</sup>Assumes an average speed of 50MPH

# **TARGET FAILURE RATES**

Description	Statistics
Acceptable risk (no further improvement required)	1:1,000,000 <sup>1</sup>
US population (2015)	>321,000,000
Traffic deaths	35,092
"Acceptable" deaths as per guidelines	321
Required improvement	x100

#### Wide variety of targets in industry Target risk reduction of 2x to 100x compared to human driver

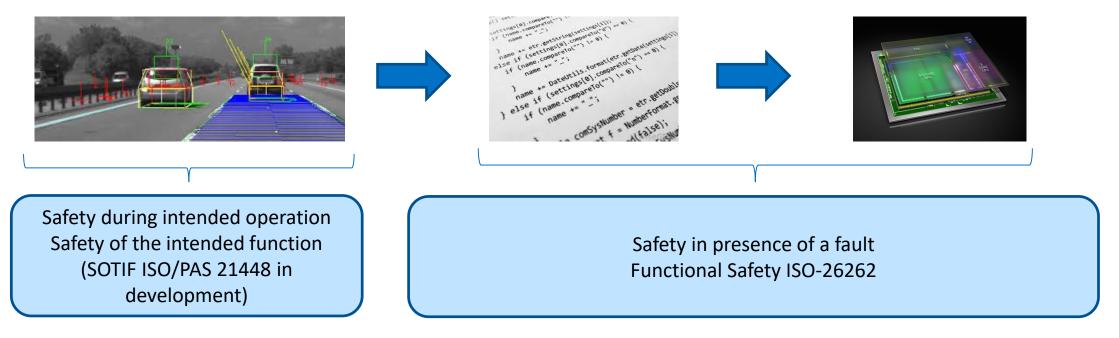
<sup>1</sup> Derived following data from UK health and safety executive publications

# SAFETY AND AUTONOMOUS VEHICLES

Algorithms

Software

Hardware



#### **FUNCTIONAL SAFETY BASICS**

# **DEFINITION PER STANDARDS**

"Absence of unreasonable risk due to hazards caused by malfunctioning behavior of electrical/electronic systems" - ISO 26262-1:2011; 1.51

"Part of overall safety relating to the equipment under control and the equipment under control, control system that depends on the correct functioning of the electrical/electronic/programmable electronic safety-related systems and other risk reduction measures" - IEC 61508-4:2010; 3.1.12

#### CLASSIC EXAMPLE IEC 61508-0:2005; 3.1

- Consider a motor winding which may overheat and cause a hazard.
- Reliability engineering approach might design the winding to be more resilient to over-temperature conditions
- Functional safety engineering approach might add a temp sensor to detect the over-temperature condition and switch off the motor



https://upload.wikimedia.org/wikipedia/commons/0/0f/Stator\_Winding\_of\_a\_BLDC\_Motor.jpg



# ACHIEVING FUNCTIONAL SAFETY

Systematic and random faults must be considered

Systematic faults mitigated by:

Following compliant process at all stages of development

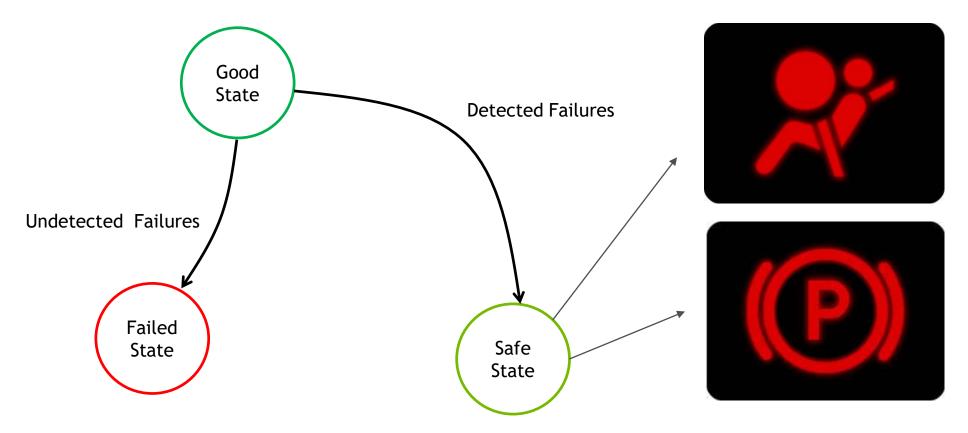
Monitoring of the complete product lifecycle

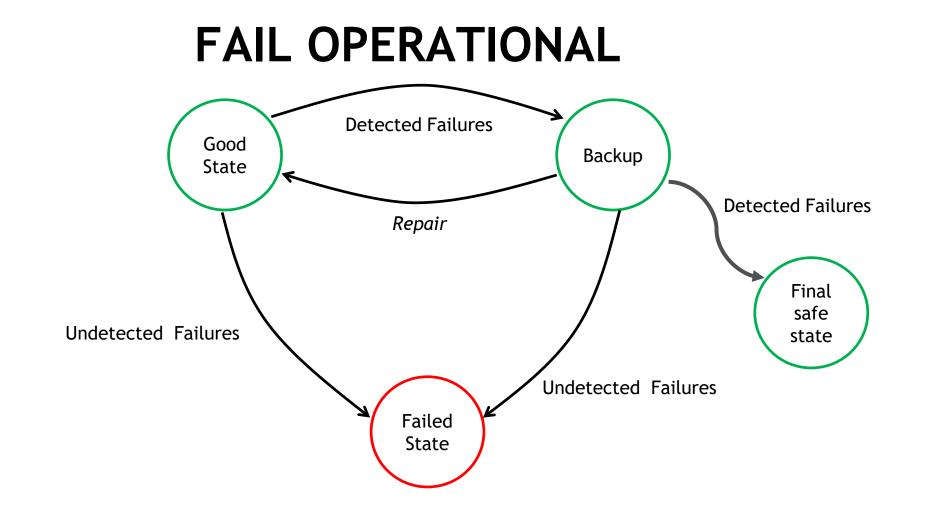
Random faults are mitigated by:

Failure mode analysis to understand the fault behavior of the system Application of diagnostic measures to detect the failure modes

Transition to the safe state on failure mode detection

## FAIL SAFE

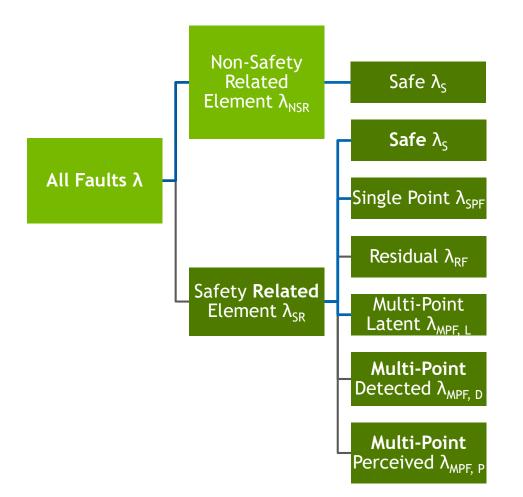




For full autonomy the initial "safe state" can be a transition to the backup system

# FAULT CLASSIFICATIONS

#### ISO 26262-10; B.1

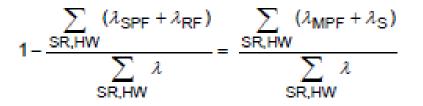


# SINGLE POINT FAULT METRIC (SPFM)

Shows the percentage of overall single point faults which are:

Safety related AND

Safe OR dangerous but detected



 $\lambda_s$  - safe fault failure rate, can also be expressed as a % (Fsafe) the ration of overall possible faults which are safe.

# LATENT FAULT METRIC (LFM)

Shows the percentage of overall multiple point faults which are:

Safety related AND

Safe OR dangerous but detected OR dangerous but perceived

Customarily limited to scenarios considering 2 point independent faults

Primary consideration is fault in mission logic combined with fault in safety mechanism

$$1 - \frac{\sum_{\text{SR,HW}} (\lambda_{\text{MPF,latent}})}{\sum_{\text{SR,HW}} (\lambda - \lambda_{\text{SPF}} - \lambda_{\text{RF}})} = \frac{\sum_{\text{SR,HW}} (\lambda_{\text{MPF,perceived or detected}} + \lambda_{\text{S}})}{\sum_{\text{SR,HW}} (\lambda - \lambda_{\text{SPF}} - \lambda_{\text{RF}})}$$

# **ARCHITECTURAL METRIC TARGETS**

	ASIL A	ASIL B	ASIL C	ASIL D
SPFM	N/A	>=90%	>=97%	>=99%
LFM	N/A	>=60%	>=80%	>=90%

All targets are recommendations. Developers can set their own targets based on appropriate argumentation.

## **PROBABILISTIC METRICS**

Probabilistic Metric for (Random) Hardware Failure (PMHF)

Examines the residual probability of violation of safety goal after application of diagnostics, in a given time of operation.

Some pushback in market due to inconsistency between methods used by different vendors.

NOTE: Multiple versions of equation possible depending on conditional probability of failures. Simplest form shown

$$M_{\rm PMHF} = \lambda_{\rm RF} + \lambda_{\rm m,DPF} \times \lambda_{\rm sm,DPF,latent} \times T_{\rm Lifetime}$$

ISO 26262-10:2011; 8.3.3

### **PMHF TARGETS**

	ASIL A	ASIL B	ASIL C	ASIL D
PMHF	N/A	100 FIT	100 FIT	10 FIT

All targets are recommendations. Developers can set their own targets based on appropriate argumentation.

## **RELEVANCE TO GPU**

# EXAMPLES OF SAFETY CRITICAL OPERATION ON GPU

#### **TRADITIONAL CV**

Normalize gamma and color

Compute gradients

Weighted voting

Contrast and normalize

Collect HOGS

Traditional Classification: (pattern and template matching)

#### **MACHINE LEARNING\***

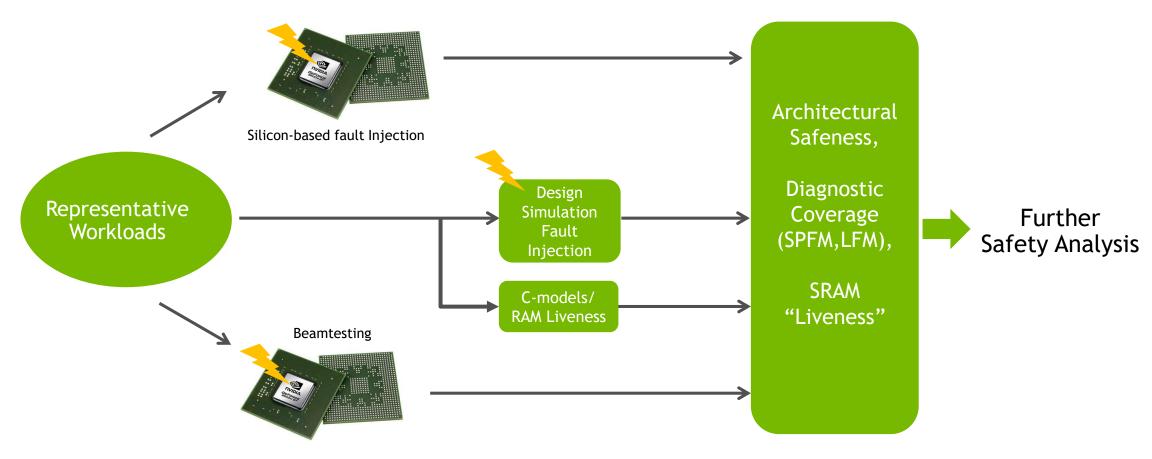
CNN (Convolutional Neural network)

MLP (Multi-layer perceptron)

SVM (Support vector machine)

\*Focus is inferencing, training handled analogously to validation and calibration of a traditional safety related algorithm.

## **GPU MEASUREMENT METHODOLOGIES**



Much of the measurement is done on representative kernels as the final applications are not available at design time

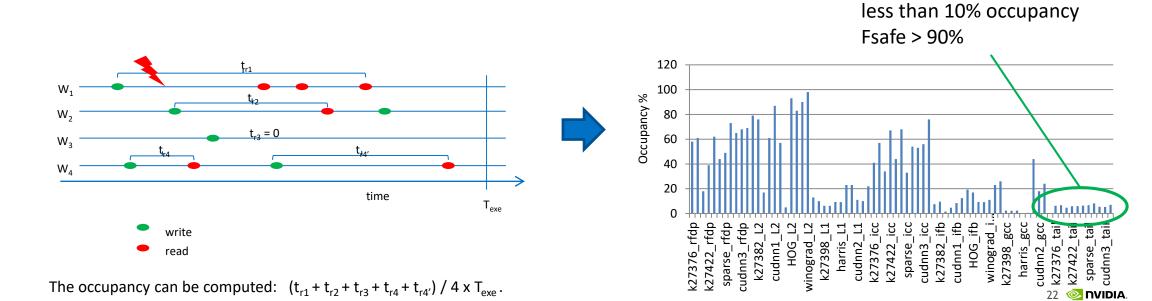
#### MEASURING SAFE FAULTS IN RAMS "LIVENESS"

RAMs are sensitive to particle radiation (4x larger failure rate per bit than flops)

RAM contents may not be sensitive to faults (pixels)

RAM contents may be very sensitive to faults (instructions)

An important indicator is RAM Liveness



Majority of RAMS in this GPU

# **TESTING REPRESENTATIVE KERNELS**

Parameter measurement is very sensitive to kernel definition

Traditional CV has a wide diversity of operations

Difficult to define representative kernels

Machine learning has a smaller set of repeated operations

Enabling a more complete definition of kernels for measurements

More accurate and reliable measurements

# **DEEP LEARNING APPLICATION SAFENESS**

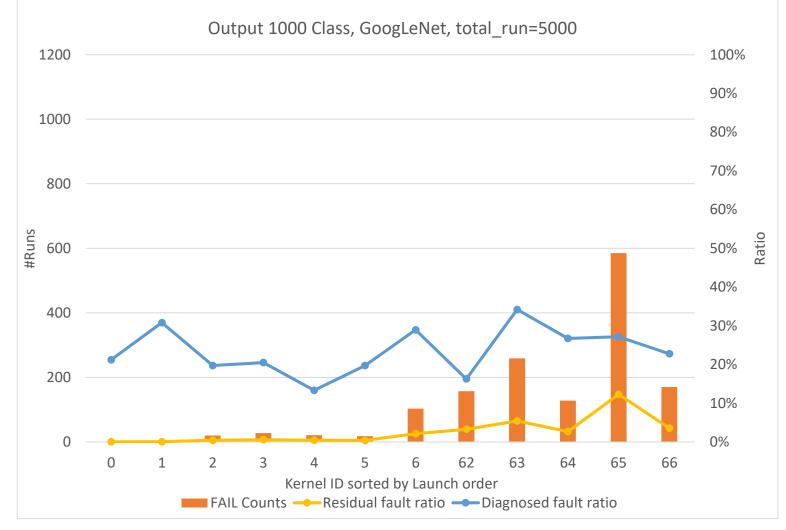
GIE GoogLeNet

67 kernels in GoogLeNet inference

Faults in latter kernels have a higher possibility to cause errors

#FAIL Counts represents the proportion of faults for which the application predicted the wrong final class

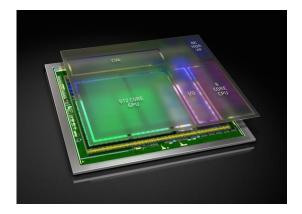
Weighted average safeness is >99 %



#### SAFETY SUPPORT IN NVIDIA GPUS

## SYSTEMATIC DEVELOPMENT OF GPU HARDWARE

Selected GPU cores targeted for automotive usage are developed with a process for ISO 26262 compliance





# LAYERED SAFETY MECHANISMS

Redundant execution

HW machine checks

Parity/ECC protection of key structures

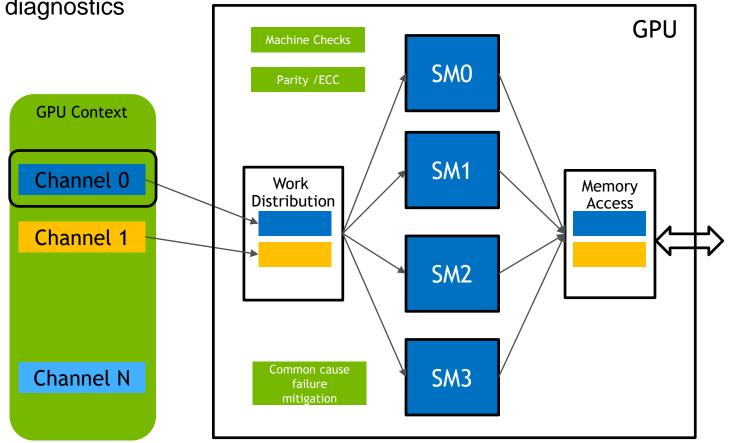
HW plausibility checks enabling multiple execution checks throughout the GPU,

Protection of large safety related memories,

Dependent failure mitigation; mainly caches and shared structures,

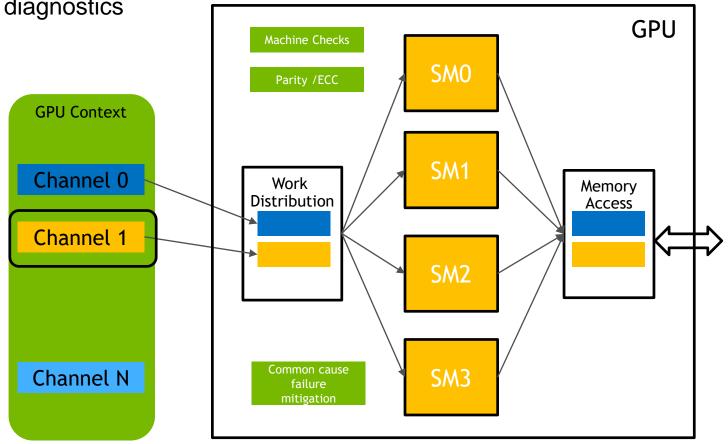
## FLEXIBLE REDUNDANCY MODEL

Flexible Execution model Built-in HW and SW diagnostics



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# SYSTEMATIC CONSIDERATIONS

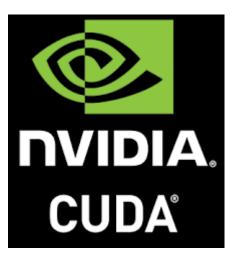
#### Software and tools

Software in the runtime is under development for ISO 26262 compliance





Software used in development (training) considered as off-line tools per ISO 26262



## **GPU FAULT MITIGATION**

# CONCLUSIONS

Nvidia is developing selected GPUs for compliance to ISO 26262

Nvidia has multiple unique capabilities to analyze safety-related performance of GPUs

Analysis to date indicates DNNs have a high degree of internal redundancy that results in high ratio of safe faults

Selected GPUs are being built with additional hardware and software diagnostic mechanisms

Nvidia is developing software and tools needed to support safety related development

