Appendix A — Project Proposal

Neuromorphic SFSVC Engine for Real-Time Drone Crack Inspection

AuraSense Limited | AISS Application 2026

Slide 1: Executive Summary

The Problem

- Hong Kong's ageing infrastructure (4,200+ bridges, 2 international airports, 2,000+ km of roads) requires frequent crack inspection
- Current methods rely on manual visual inspection or cloud-dependent video streaming
- Cellular bandwidth costs for drone video: **$1,040/drone/month** (H.265 @ 30fps)
- Cloud dependency creates single points of failure for safety-critical inspection

Our Solution

SFSVC — a neuromorphic video middleware that converts video into sparse spike events on-device, enabling:
- **94% bandwidth reduction** ($64/drone/month vs $1,040)
- **Sub-millisecond** crack detection latency
- **Zero cloud dependency** — full on-device intelligence
- **Inspection-grade accuracy** — 98.7% crack detection match

AISS Request

- **2 GPU Cards** for **6 months** starting June 2026
- Purpose: Train neuromorphic encoders, crack detection models, and YOLO semantic modules

Slide 2: Project Milestones & Timeline

## 6-Month Implementation Plan (Jun – Nov 2026)
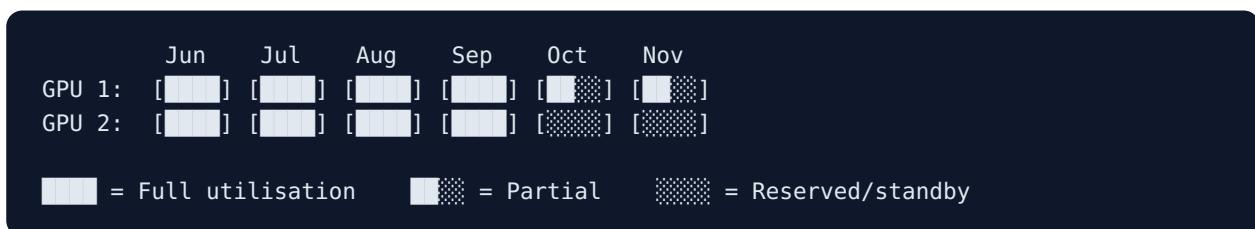
MONTH	MILESTONE	GPU USAGE	DELIVERABLE
M1 (Jun)	Dataset preparation & baseline training	2 GPUs — full utilisation for encoder pre-training	Curated dataset (runway, road, bridge cracks)
M2 (Jul)	Neuromorphic encoder training & optimisation	2 GPUs — encoder + spike model training	Trained spike encoder v2 with FP16 optimisation
M3 (Aug)	Crack perception model training	2 GPUs — crack detector fine-tuning	Production-grade crack perception module
M4 (Sep)	YOLO semantic module training + RT integration	2 GPUs — YOLO training + simulation sweeps	YOLO-integrated multi-rate SFSVC engine
M5 (Oct)	System integration & pilot validation	1 GPU — inference testing + stress simulations	Pilot-ready SDK package
M6 (Nov)	Benchmark, documentation & pilot deployment	1 GPU — final benchmark runs	Full benchmark report + pilot demo

Key Gates

- **Gate 1 (M2):** Spike encoder achieves ≥90% sparsity with <2% accuracy loss
- **Gate 2 (M4):** End-to-end latency <6ms on Jetson with YOLO semantics
- **Gate 3 (M6):** Passed pilot validation at ≥1 Hong Kong infrastructure site

Slide 3: Computing Power Requirement & Justification

GPU Allocation Plan (2 GPU Cards × 6 Months)

```
            Jun    Jul    Aug    Sep    Oct    Nov
GPU 1:  [████] [████] [████] [████] [██▒▒] [█▒▒▒]
GPU 2:  [████] [████] [████] [████] [▒▒▒▒] [▒▒▒▒]

 ████ = Full utilisation    █▒▒ = Partial    ▒▒▒▒ = Reserved/standby
```

Training Workload Breakdown

WORKLOAD	GPU HOURS	GPU(S)	DURATION
Neuromorphic spike encoder pre-training	~1,440 hrs	2	M1–M2
Crack perception model fine-tuning	~720 hrs	2	M3
YOLOv8-nano semantic detector training	~720 hrs	2	M4
Large-scale simulation sweeps (latency/robustness)	~480 hrs	1	M4–M5
Benchmark & validation runs	~240 hrs	1	M5–M6
Total	**~3,600 GPU-hours**		

Justification

- **Encoder training** is the most GPU-intensive: event-based temporal convolutions over video sequences of 1,000+ frames require large batch processing and mixed-precision (FP16/FP32) training
- **Simulation sweeps** test the engine under 100+ combinations of lighting, weather, motion speed, and network conditions — impossible on CPU alone
- **Two GPUs** enable parallel experimentation (e.g. training encoder on GPU 1 while running crack detector ablation on GPU 2)

Other ICT Infrastructure Requirements

RESOURCE	SPECIFICATION	JUSTIFICATION
Storage	2 TB NVMe SSD	Crack datasets (100+ GB) + model checkpoints + simulation logs
RAM	64 GB	Large batch training + data pipeline buffering
OS	Ubuntu 22.04 LTS	PREEMPT_RT kernel support + CUDA compatibility
Framework	PyTorch 2.x + CUDA 12	Neuromorphic model training; TensorRT for deployment
Networking	10 Gbps internal	High-speed data loading from storage to GPU

Slide 4: Market Analysis

Target Market: Autonomous Infrastructure Inspection

Hong Kong & GBA Addressable Market

SEGMENT	HK MARKET	GBA MARKET	KEY NEED
Airport runway inspection	HK$50M/yr	HK$200M/yr	Real-time, safety-critical
Bridge & tunnel inspection	HK$80M/yr	HK$500M/yr	Hard-to-access, high-risk
Road surface monitoring	HK$30M/yr	HK$300M/yr	Large-area, cost-sensitive
Building façade inspection	HK$40M/yr	HK$150M/yr	Urban density, regulatory
Total TAM	**HK$200M/yr**	**HK$1.15B/yr**	

Competitive Landscape

SOLUTION	LATENCY	BANDWIDTH	EDGE-READY	NEUROMORPHIC
AuraSense SFSVC	**<1 ms**	**-94%**	􀆅	􀆅
Cloud YOLO (AWS/Azure)	50–200 ms	0% saving	􀆅	􀆅
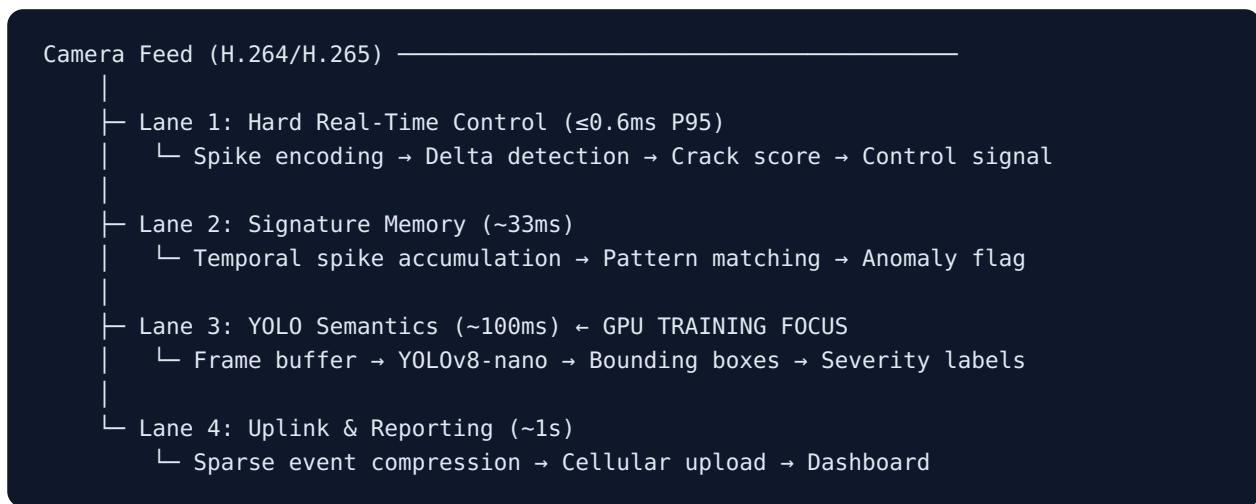
SOLUTION	LATENCY	BANDWIDTH	EDGE-READY	NEUROMORPHIC
Edge YOLO (Jetson)	5–15 ms	0% saving	☐	☐
Event cameras + SNN	1–5 ms	-80%	☐	Partial
H.265 + cloud analytics	100+ ms	-50% (codec)	☐	☐

SFSVC Unique Advantage

Our approach is the **only solution** combining neuromorphic spike encoding, sub-millisecond control latency, and 94% bandwidth reduction in a single middleware — no special hardware (event cameras) needed.

Slide 5: R&D Methodology — Neuromorphic Engine Architecture

SFSVC Multi-Rate Four-Lane Architecture

```
Camera Feed (H.264/H.265) ─────────────────────────────
    │
    ├─ Lane 1: Hard Real-Time Control (≤0.6ms P95)
    │    └─ Spike encoding → Delta detection → Crack score → Control signal
    │
    ├─ Lane 2: Signature Memory (~33ms)
    │    └─ Temporal spike accumulation → Pattern matching → Anomaly flag
    │
    ├─ Lane 3: YOLO Semantics (~100ms) ← GPU TRAINING FOCUS
    │    └─ Frame buffer → YOLOv8-nano → Bounding boxes → Severity labels
    │
    └─ Lane 4: Uplink & Reporting (~1s)
         └─ Sparse event compression → Cellular upload → Dashboard
```

Training Pipeline (GPU-Accelerated)

1. **Spike Encoder Training**
   - Input: Video pairs (frame_t, frame_t+1) from crack datasets
   - Output: Optimised threshold parameters, temporal kernels
   - Method: Self-supervised contrastive learning on spike representations
   - GPU need: Mixed-precision training, batch size 32–64

2. **Crack Perception Training**
   - Input: Labelled crack image datasets (CrackForest, DeepCrack, custom runway data)
   - Output: Lightweight crack classifier operating on spike features
   - Method: Transfer learning from pre-trained backbone → spike-domain fine-tuning

3. **YOLO Semantic Training**
   - Input: Annotated inspection images with crack bounding boxes + severity labels
   - Output: YOLOv8-nano model optimised for TensorRT deployment on Jetson
   - Method: Progressive training (pre-train on COCO → fine-tune on crack dataset)

4. **System Simulation**
   - Monte Carlo sweeps over 100+ parameter combinations
   - Validate latency, accuracy, and bandwidth under degraded conditions

Slide 6: R&D Methodology — Detailed Technical Approach

Current Proven Performance (Internal Benchmarks)

METRIC	RESULT	TEST CONDITIONS
P50 Latency	**0.40 ms**	1280×720, 30fps, 1,127 frames
P95 Latency	**0.56 ms**	Same
Throughput	**125 fps**	6 processing lanes
Sparsity	**93.8%**	6.84M spikes across 1.127M pixels/frame
Bandwidth Saving	**94%**	vs H.265 @ 5.2 Mbps
Crack Accuracy	**98.7%**	vs manual labelling
False Positive Rate	**<0.3%**	

GPU-Enabled Improvements Targeted

CURRENT STATE	AISS-ENABLED TARGET	HOW
Hand-tuned spike thresholds	Learned adaptive thresholds	GPU-trained encoder
Rule-based crack scoring	Neural crack perception	CNN on spike features
No semantic labels	YOLO severity classification	YOLOv8,nano training
Fixed parameters	Adaptive to scene conditions	Simulation sweeps on GPU
Single resolution tested	Multi-resolution validated	Parallel GPU experiments

Key Innovation: Bio-Inspired Temporal Coding

SFSVC's spike encoding mimics biological retinal ganglion cells:
- **ON spikes:** Brightness increase > threshold (delta > 8 gray levels)
- **OFF spikes:** Brightness decrease > threshold
- **Encoding:** AVX2-accelerated, 32 pixels per SIMD register
- **Result:** 93.8% of pixels produce zero spikes (sparse) → massive bandwidth reduction

This aligns with the **14th Five-Year Plan** priority on **Brain Science and Brain-Like Technology Research**.

Slide 7: Risk Assessment

Technical Risks

RISK	LIKELIHOOD	IMPACT	MITIGATION
Trained encoder underperforms hand-tuned	Medium	Medium	Keep hand-tuned as fallback; progressive training with ablation
YOLO semantic lane exceeds latency budget	Medium	Low	Lane 3 operates asynchronously; does not block control lane
Insufficient crack dataset diversity	Low	High	Synthetic augmentation (rotation, lighting, blur) + partner data

RISK	LIKELIHOOD	IMPACT	MITIGATION
Edge hardware (Jetson) memory constraints	Medium	Medium	INT8 quantisation + TensorRT optimisation

Operational Risks

RISK	LIKELIHOOD	IMPACT	MITIGATION
Key person dependency (1-person team)	High	High	Modular codebase + comprehensive documentation; recruitment planned upon funding
Pilot partner delays	Medium	Medium	Multiple parallel discussions; can demo on synthetic data first
IP disclosure during pilot	Low	High	Provisional patent filed; NDA with all partners

Financial Risks

RISK	LIKELIHOOD	IMPACT	MITIGATION
GPU costs exceed subsidy duration	Low	Medium	Efficient training schedule; early stopping; model distillation
No revenue during R&D phase	High	Medium	Low burn rate (1-person); AISS covers compute; seeking angel round

Slide 8: Market Entry & Business Model

Go-to-Market Strategy

Phase 1: Pilot Validation (M1–M6, AISS Period)

- Validate with 1–2 Hong Kong infrastructure partners (airport/bridge)
- Free pilot deployments to build reference cases
- **Output:** Benchmark data, testimonials, case studies

Phase 2: Commercial Launch (M7–M12)

- Subscription pricing: **$500–$1,000/drone/month** (SDK + support)
- Target: 10–30 drone fleet operators in HK & GBA
- **Revenue target:** HK$300K–$900K/month by end of Year 1

Phase 3: Scale (Year 2+)

- Platform licensing to system integrators
- Expand to ground robots, fixed CCTV, autonomous vehicles
- GBA and international expansion

Business Model

REVENUE STREAM	PRICING	TARGET CUSTOMERS
SFSVC SDK License	$500–$1,000/drone/month	Drone fleet operators
Pilot & Integration	$50K one-time	Infrastructure owners
Enterprise Platform	Custom	System integrators

Unit Economics (30-drone fleet)

- **Customer pays:** $15,000–$30,000/month
- **Customer saves:** $29,280/month on bandwidth alone
- **ROI for customer:** Positive from Month 1

Slide 9: Team Structure & Qualifications

Core Team

Chau Kai Cho (周啟祖) — CEO & Lead Engineer

- **Role:** Full-stack R&D — architecture, C++ engine, ML training, pilot integration
- **Background:**
- Deep expertise in real-time systems, neuromorphic computing, and edge AI
- Designed and implemented the complete SFSVC engine in C++ with AVX2 SIMD optimisation

- Built the four-lane multi-rate architecture from first principles
- Filed provisional patent for spike-based neuromorphic video encoding
- **Technical Achievements:**
- 0.40ms P50 latency (125 fps) on 1280×720 video — fully functional prototype
- Complete C++/Python SDK with pybind11 bindings
- Lock-free queue architecture for real-time multi-lane processing
- Hardware profiler, degraded mode policy, and failsafe subsystems

Planned Hiring (Post-Funding)

- **ML Engineer** (1 FTE) — focus on spike encoder and YOLO model training
- **Embedded Engineer** (1 FTE, contract) — Jetson/ARM deployment and optimisation

Organisational Chart

```
CEO / Lead Engineer (Chau Kai Cho)
    ├── R&D: Neuromorphic Engine & Architecture
    ├── R&D: ML Model Training (GPU) — to hire
    └── Engineering: Edge Deployment — to hire (contract)
```

Slide 10: Summary & Expected Impact

Project Summary

ITEM	DETAIL
Applicant	AuraSense Limited (HK AI start-up)
Project	Neuromorphic SFSVC Engine for Drone Crack Inspection
GPU Request	2 GPU Cards × 6 Months
Start Date	1 June 2026
Key Deliverable	Production-grade SFSVC SDK + Pilot Deployment

Expected Impact

For Hong Kong I&T Ecosystem

- First neuromorphic edge AI middleware originating from Hong Kong
- Reference implementation for brain-inspired computing research
- Bridges academic neuroscience concepts into commercial deployment

For Hong Kong Economy & Society

- Safer infrastructure inspection (reduces manual high-risk work)
- New market opportunities in smart airports, GBA logistics corridors
- Positions HK as a testbed for neuromorphic AI + autonomous systems

Measurable Outcomes

- **1 patent** filed (provisional → full)
- **1–2 publications** in neuromorphic computing / real-time AI
- **≥1 pilot** validated with HK infrastructure partner
- **94% bandwidth reduction** demonstrated in production conditions
- **Sub-6ms latency** with GPU-trained models on edge hardware

Alignment with National Priorities

14TH FIVE-YEAR PLAN AREA	THIS PROJECT'S CONTRIBUTION
Artificial Intelligence	Production neuromorphic AI for autonomous inspection
Brain Science & Brain-Like Technology	Bio-inspired spike encoding architecture

AuraSense Limited — Building the neural system for autonomous infrastructure inspection
Contact: Dicksonchau@aurasensehk.com | +852 9291 8674