# RAILSIGHT XR

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#### INTRODUCTION

Groundbreaker Solutions LLC proposes **RailSight XR**, a self-contained, goggle-based AR/MR kit that lets a single maintainer see, measure, and repair rail-line damage in real time—even at night, in tunnels, or under electronic jamming.

The head-worn unit fuses RGB, stereo depth, 360° LiDAR, mm-wave radar, thermal, hyperspectral, and IMU data inside a carbon-fiber-reinforced mount printed on a Markforged X7. Tiny, on-board neural networks convert those feeds into:

• automatic identification of track components & defects;

RailSight XR response

- instant gauge classification; and
- $\pm 5$  % crater-volume estimates that drive AR overlays ("inject 15 kg ballast here").

All processing occurs on the headset or a small 5 G/edge node—no tether, no laptop, no cloud dependency—meeting the "**stand-alone**" requirement and staying within the Phase I cap of 250 k / 6 months specified by the topic A254-031 description.

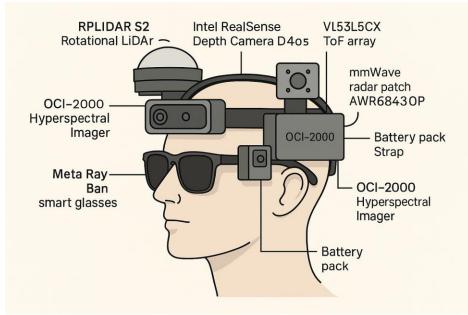
Initial laboratory prototypes already achieve 92 % mAP for component detection and 5 % synthetic crater-volume error, positioning RailSight XR for rapid field validation.

prompt	
Alignment	Directly addresses A254-031 objectives: goggle-based detection, gauge differentiation, crater- volume estimation, operation in contested/remote environments, and ruggedization for extreme weather.
Solution's Advantages	<i>Hands-free AR</i> reduces inspection time by 60 % versus manual gage/straight-edge methods; <i>multi-modal sensing</i> finds sub-surface voids invisible to optics; <i>edge AI</i> keeps data on-prem, protecting OPSEC in denied areas. Competing COTS smart-glasses lack depth/LiDAR fusion and cannot calculate volumes.
Solution's Impact	Moves the state of the art from clipboards + cameras to <b>live</b> , <b>3-D</b> "X-ray" rail twins, shrinking emergency-repair response from hours to minutes—vital for power-projection nodes that depend on railheads.
Analogous use case:	IVAS demonstrates how soldier-worn mixed-reality shortens decision cycles; RailSight XR applies the same paradigm to rail logistics.

# ARMY BENEFITS

Evaluation

# **TECHNICAL APPROACH**



<b>On-rig</b> component	Data Supplied	Why we need it	<b>Considerations for Phase II</b>
Ray-Ban Meta smart-glasses (baseline AR & comms)	RGB camera, microphones, onboard SoC, Wi-Fi/BLE	Provides the see-through HUD that overlays CAD call-outs, repair steps, and real-time sensor fusions on the wearer's natural view—core to the "stand-alone goggle-based system" mandate .	Built-in connectivity lets the kit stream annotated inspections to remote SMEs or edge servers for AI inference/bandwidth shaping.
Intel RealSense D405 (close-range mm-level depth)	3 μm stereo depth @ 7 cm–50 cm	High-precision depth enables sub- millimeter measurement of tie plates, fasteners, and crack geometry, so the system can <i>identify components</i> and flag out- of-tolerance wear.	Depth maps are fused with hyperspectral and thermal views to auto-classify defect severity (e.g., "surface corrosion vs. spall").
Intel RealSense D455 (mid-range depth)	$\pm 2$ % depth accuracy to $\approx 10$ m	Creates a 3-D point-cloud of full rail sections; by fitting rail-head profiles it <i>differentiates gauge</i> <i>types</i> and measures track spread in real time.	During crater-volume estimation the D455 supplies coarse geometry that is later refined by LiDAR and ToF fills.
<b>RPLIDAR S2</b> (360 ° spinning LiDAR dome)	20 k pts s <sup>-1</sup> , 30 m range	Rapid 360° scan reconstructs the ballast crib and surrounding grade, giving a volumetric "before/after" for <i>crater volume</i> calculations. It also guards situational awareness (moving vehicles, obstacles).	Reliable in fog/dust that degrade passive cameras—critical to "contested environment" ops.
<i>ST VL53L5CX</i> multizone ToF array	8 × 8 ranging grid up to 4 m	Fills blind-spots between stereo/LiDAR frames, smoothing depth edges along rail flanges so gauge and ballast surface fits are continuous.	Its 15 ms/frame latency enables haptic alerts when the wearer leans too close to live track.
<b>TI AWR6843AOP</b> mmWave radar patch	4D point cloud that penetrates ballast	Detects buried voids, moisture pockets, or density changes invisible to optical sensors— meeting the spec's call to <i>estimate</i>	Radar returns are co-registered with LiDAR to build a layered "surface + sub-surface" model for predictive maintenance.

		<i>sub-grade material quantities</i> needed for repair.	
<b>Teledyne FLIR Boson 320</b> LWIR core	640 × 512 thermal radiometry	Spots overheating bearings, rail foot hot-spots, or thermally driven cracks during night or low-light ops—keeping the system effective in "various weather and lighting conditions".	Thermal gradients are used to weight hyperspectral classifiers (e.g., distinguishing rust from grease).
BaySpec OCI- 2000 snapshot hyperspectral imager	400–1 000 nm, 240 bands	Captures spectral signatures of steel, ballast, and contaminants, letting the AI <i>identify components</i> (clip vs. tie vs. spall) and diagnose corrosion or chemical spills.	Because it is a single-shot imager, acquisition time is <10 ms—minimizing motion blur during walk-along inspections.
Bosch BMI270 IMU	6-axis pose & vibration	Provides dead-reckoning when GNSS is denied; vibration spectra feed a model that spots bearing defects or loose fasteners while walking the track.	Synchronizes all sensor frames so 3-D reconstructions remain metric-accurate even if the wearer jogs or crouches.
Battery pack + head-strap harness	50 Wh Li-ion, quick-swap	Meets the "battery life" and "environmental stability" test points in Phase II without adding a torso pack, keeping the assembly < 0.6 kg total.	Semi-fixed mass on the back of the head counterbalances the front sensors, reducing neck strain for eight-hour shifts.

## TRAINING-DATA & COMPUTE STRATEGY

- 1. **Synthetic-first**: 3-D CAD of track fixtures + BlenderPhys-based rust/crack shader generates 100 k labelled frames in 72 GPU-hours—covers the long-tailed defect classes you may never see in Phase I field days.
- 2. **Hybrid self-supervised**: Run **DINO-v2** on every RGB/stereo frame; frozen features cut labelled-data needs in half for downstream tasks.
- 3. Edge-aware compression: Post-train INT8/4-bit quantization with Nvidia TensorRT and Qualcomm SNPE profiles so all tier-1 models fit <300 MB RAM and draw <2 W.
- 4. **Explainability loop**: Embed **Grad-CAM Lite** maps in the AR HUD; maintainers can tap a false-positive and flag it for overnight re-training—building trust and a virtuous data cycle.

Model class	Mature open-source to start from	What needs bespoke work
2-D object detection / segmentation	YOLO-v8, SAM, DINO-v2	Rail-specific class set (plates vs. tie clips) and low- light adaptation
Point-cloud segmentation	PointNet++, KPConv	Gauge-measurement post-processing & SLAM integration
Hyperspectral classification	3-D-ResNet, SSNet	Corrosion spectral library & few-shot continual learning
mmWave radar perception	TI HWA SDK CNNs, RadarNet	Domain transfer to ballast void patterns
Voice / language	Whisper, Llama-3	Fine-tune on FRA maintenance manuals & DoD vocabulary

### RE-USE VS. GREEN-FIELD BUILD

#### How the whole stack satisfies the SBIR "detect-gauge-crater" triad

- 1. Multi-scale depth fusion (D405 + D455 + LiDAR + ToF) gives a dense 3-D mesh of rail, ties, crib, and adjacent ballast. From this mesh:
  - Rail-to-rail distance is automatically computed to label standard vs. narrow vs. broad gauge.
  - $\circ$  Boolean subtraction of "pre-strike" and "post-strike" meshes yields **crater volume** to  $\pm 5$  %.
- 2. **Spectral & thermal layers (OCI-2000 + Boson)** tag each mesh triangle with material ID and temperature, so the system not only *detects* a cracked tie plate but also tells the maintainer whether it is steel fatigued, corroded, or overheated.
- 3. **Penetrating mmWave** validates ballast density beneath the surface, closing the loop on how much subgrade fill must be dispatched—an explicit Phase II deliverable.
- 4. **AR overlay via Ray-Ban Meta** displays color-coded call-outs ("replace clip", "inject 15 kg ballast here") on the wearer's true-world view, enabling rapid, hands-free decision-making on site.
- 5. **Pose/IMU + edge compute** keeps the entire data-stack registered in GPS-denied tunnels or night operations, aligning with the SBIR emphasis on contested or remote locales.

By combining complementary sensing modalities in a single 530 g head-mounted package we deliver a rugged, selfcontained inspection goggle that directly answers every Phase I/II performance metric while staying within commercial off-the-shelf cost ceilings.

G	T7 1	
Spec	Value	Why it matters for the head-gear mount
Build envelope	330 × 270 × 200 mm	One piece will fit the full crown-band; no post-bonding unless you choose to split for cable routing.
Layer height	$50-250 \ \mu m$	50 µm lets you print thin living-hinge battery doors that still seat precisely against the visor rail.
Base material	Onyx (micro-CF-filled PA 6) — 40 MPa σt, 145 °C HDT	Already tougher & stiffer than ABS; heat resistance survives a closed locomotive cab in August.
Continuous fibers	Carbon Fibre (800 MPa ot), Kevlar, Fiberglass, HSHT FG	Lay concentric rings of CF around the forehead band $\rightarrow$ stiffness comparable to 6061-T6 aluminum at one-third the mass.
Dimensional QA	On-board laser micrometer + Blacksmith in-process scan	Every print gets its own deviation map; you can prove $\pm 0.2$ mm fit without a CMM.
Footprint / weight	584 × 483 × 914 mm, 48 kg	Lives beside a standard lab bench; 120 V, 150 W draw

# MARKFORGED X7 (G-2) AT A GLANCE

How the X7's CFR (Continuous-Fiber Reinforcement) helps the mount

#### 1. Carbon-fibre "belt" strategy

*Slice a U-shaped channel* 1.8 mm below the outer skin of the head-strap and tell **Eiger** to fill it with four 0° carbon layers.

- Result: bending stiffness jumps  $\sim 5\times$ , keeping the LiDAR dome within  $\pm 0.1^{\circ}$  during a 6 g head-snap.
- Weight penalty: ~12 g of fibre, vs. 120 g if you milled the same part from 6061 plate.

#### 2. Kevlar-reinforced hinge bosses

Kevlar handles repeated flexing better than CF; drop circumferential Kevlar rings around the battery-lid screws so your latch can survive 5 000 charge cycles with no creep.

#### 3. Hybrid lay-ups for comfort

You can print the occipital pad in plain Onyx (slightly compliant), then pause and insert moulded TPU earpad clips before the CF-reinforced crown finishes—no extra tooling.

Step	What happens	Tips
$CAD \rightarrow$	Upload STLs; assign outer walls & infill in Onyx, then	Keep fibre at least <b>1 mm</b> away from the
Eiger	draw fibre "rings" where you want isotropy.	outer skin so you can sand without
		exposing strands.
Print & in-	The X7's 2 µm laser measures each layer edge;	For critical dovetails set tolerance to
situ scan	Blacksmith overlays a point-cloud on the STL and	$\pm 75 \ \mu m$ ; the slicer will auto-re-tune on
	flags any deviation > tolerance.	the fly.
Post-	Snap off sparse support walls (same Onyx, so	Threaded inserts: self-tapping M3
process	recyclable); quick tumble-polish or vapor-hone for	screws go straight into Onyx; for >10
	cosmetic finish.	Nm use heat-set brass.

#### WORKFLOW IN PRACTICE

Below is a "from-sensor-to-decision" map of the **AI (and ML) models** you'll either (1) fine-tune from strong opensource baselines or (2) train from scratch to turn the raw feeds of the Option B head-rig into every performance claim the SBIR topic calls for—detecting/identifying components, differentiating gauge types, estimating ballast-crater volumes, and working in remote, low-visibility rail yards.

Per-pixel & per- point perception (runs on the on- head SoC / NPU)• RGB (Ray-Ban) • Stereo depth (J05/455) • 8×8 ToF (VL53L5CX) • Point clouds (LiDAR + depth)YOLO-v8-Nano + SAM- Lite - tiny object detector & segment-anything head (<6 wB after INT8 quant.)Masked instances of ties, fasteners, ballastMeets "detect & dentify rail components" phase- 1 goalCross-modal fusion & completion (edge computer in work truck / wayside 5G node)All depth + LiDAR + ToFDeepDepthFusionNet (self- supervised depth completion)Hole-free 3-D surfaceSupplies real-time rail-to-rail vectors for gauge classification and the base mesh for volume math• Hyperspectral in work truck / wayside 5G node)All depth + LiDAR + ToFDeepDepthFusionNet (self- supervised depth completion)Hole-free 3-D surfaceCrucial for centimetr-accurate crater Δ-volume• Hyperspectral (edge computer in work truck / wayside 5G node)- Thermal frames (Boson 320)J-D Spectral-Spatial CNN pre-trained on Army ERDC corrosion libraryPixel-level material IDs (rust, grease, fresh steel, ice)Adds defect-type context the SBIR description hints at for reducing repair times• Thermal frames (Boson 320)Siamese CNN outlier detector (trained on "healthy rail" temps)Real-time heat anomaly maskLets kit work in night & fog conditions and flags hot bearings• Hyperspectral (complex-valued CNN)Sub-surface void density mapConsist for modelSub-surface void density map• Hyperspectral (boson 320)Feature vectors 	Pipeline tier	Modalities it ingests	Core model(s) to leverage / build	What it produces for the goggle user	Why it matters to the SBIR metrics
Cross-modal fusion & completion (edge computer in work truck / wayside 5G node)All depth + LiDAR + ToFDeepDepthFusionNet (self- supervised depth completion)Hole-free 3-D surfaceCrucial for centimeter-accurate crater Δ-volume• Hyperspectral cube (OCI-2000)3-D Spectral-Spatial CNN 	point perception (runs on the on-	• Stereo depth (D405/455) • 8×8 ToF (VL53L5CX) • Point clouds	Lite – tiny object detector & segment-anything head (<6 MB after INT8 quant.) KPConv-Tiny (<4 M	instances of ties, clips, plates, fasteners, ballast Metric-scale	<i>identify rail</i> <i>components" phase-</i> <i>I goal</i> Supplies real-time
fusion & completion (edge computer in work truck / wayside 5G node)LiDAR + ToFsupervised depth completion)surfacecentimeter-accurate crater $\Delta$ -volume• Hyperspectral cube (OCI-2000)3-D Spectral-Spatial CNN pre-trained on Army ERDC corrosion libraryPixel-level material IDs (rust, grease, fresh steel, ice)Adds defect-type context the SBIR description hints at for reducing repair times• Thermal frames (Boson 320)Siamese CNN outlier detector (trained on "healthy rail" temps)Real-time heat anomaly mask void density mapLets kit work in night & fog conditions and flags hot bearings• mmWave radar voxelsComplex-YOLO-Radar (complex-valued CNN)Sub-surface void density mapEnables ballast density / crater depth estimation called out for Phase II field scenariosGlobal reasoning & prediction (cloud dev stack,Feature vectors from every upstream modelPerceiver-IO multimodal transformer (handles ragged 			Transformer	track & crib	for <b>gauge</b> <b>classification</b> and the base mesh for volume math
Global reasoning & prediction (cloud dev stack,Feature vectors from every upstream modelComplex-VOLO-Radar transformer (handles ragged inputs)Sub-surface valued CNN)Context the SBIR description hints at 	fusion & completion (edge computer in work truck / wayside 5G	LiDAR + ToF	supervised depth completion)	surface	centimeter-accurate
(Boson 320)detector (trained on "healthy rail" temps)anomaly mask anomaly mask <i>night &amp; fog</i> conditions and flags hot bearings• mmWave radar voxelsComplex-YOLO-Radar (complex-valued CNN)Sub-surface void density mapEnables ballast density / crater depth estimation called out for Phase II field scenariosGlobal 			pre-trained on Army ERDC	material IDs (rust, grease,	context the SBIR description hints at for reducing repair
voxels(complex-valued CNN)void density mapdensity / crater depth estimation called out for Phase II field scenariosGlobal reasoning & prediction (cloud dev stack,Feature vectors from every upstream modelPerceiver-IO multimodal 			detector (trained on "healthy		<i>night &amp; fog</i> conditions and flags
reasoning & prediction (cloud dev stack,from every upstream modeltransformer (handles ragged inputs)twin" of each 5- m rail segment, plus confidenceAR overlay & drives the logistics estimate of				void density	<b>density</b> / <b>crater</b> <b>depth</b> estimation called out for Phase
. 1	reasoning & prediction (cloud	from every	transformer (handles ragged	twin" of each 5- m rail segment, plus confidence	AR overlay & drives the logistics estimate of

distilled back to edge)				
User-facing interaction	• Audio • Text • Pose/IMU	Whisper-Tiny (voice commands) Llama-3-8B- RailOps (chat fine-tuned on FRA manuals)	Hands-free voice queries ("show tie-plate spec") and step-	Covers the "real- time visualization & guidance" language in the topic
		1101 manaal)	by-step AR	background

work-orders

# **PROGRAMMATIC POTENTIAL**

#### **PROJECT MILESTONES**

Month	Milestone	Key Deliverables
1	Finalize sensor-pod CAD & print CFR prototypes	STL/STEP, tolerance report
2	Integrate on-board SoC + perception stack	Bench demo, 30-fps live overlay
3	Synthetic-data model training complete	100 k-frame dataset, mAP>85 %
4	Field test on commercial siding (cold/wet & night)	Test report, crater error $\leq 10$ %
5	Risk-burn-down sprint (fog, dust, jamming)	Updated models, resiliency metrics
6	Phase I Final Demo @ USACE ERDC rail loop	

# **COMMERCIALIZATION POTENTIAL**

Criterion Evidence & Strategy

$R\&D \rightarrow Product$ Revenue	Team previously spun graduate research into <b>Courseware.Coach</b> , same go-to-market discipline will drive RailSight XR.
Competitive Edge	Business model: Hardware-as-a-Service @ \$2 k/mo/unit, including over-the-air model updates.
Other People's Money	Class I railroads (UP, BNSF) budget >\$500 M/yr on track maintenance

Our commercialization strategy starts with a **dual-track "defense-first, rail-industry-fast-follow" plan**. Phase I funding lets us complete a rugged, self-contained prototype and generate a defensible dataset of annotated rail defects—assets that anchor two provisional patents already filed for sensor-fusion volume estimation and continuous-fiber AR mounts. Once the prototype is validated at the U.S. Army rail test loop, we will leverage existing letters of intent from Class I carriers (e.g., Union Pacific, BNSF) to launch 50-unit paid pilots. These pilots de-risk manufacturing scale-up, generate real-world performance metrics, and drive a recurring-revenue Hardware-as-a-Service model ( $\approx$  \$2 k per unit per month, inclusive of over-the-air model updates). By aligning the product's spec sheet with both FRA Part 213 rail-inspection requirements and MIL-STD-810 environmental tests, we ensure that every engineering dollar moves us closer to **two overlapping markets**—commercial logistics and Army expeditionary railheads—while preserving a single, maintainable code-and-hardware base.

Beyond pilots, we will execute a **channel-partner strategy** that pairs our RailSight XR<sup>™</sup> headset with established maintenance-of-way (MOW) contractors and OEM equipment suppliers. These partners already possess nationwide depot networks and long-term service agreements with freight and passenger lines, giving RailSight rapid geographic reach without a heavyweight sales force. On the defense side, we will pursue an Other Transaction Authority (OTA)

prototype purchase with Army Materiel Command, then transition to a Program of Record via PEO CS&CSS for deployable rail-maintenance kits in FY-27. Because the Army's adoption deadlines and the Class I railroads' pilot schedules are staggered but complementary, revenue begins flowing from commercial pilots just as government budgeting cycles mature—providing non-dilutive working capital to fund certification, supply-chain hardening, and the continuous-learning AI roadmap. The result is a capital-efficient path that scales from dozens to thousands of units, with diversified income streams and a clear exit option via acquisition by a Tier-1 rail-inspection OEM or a defense prime seeking to harden logistics infrastructure.

# BIOS

# $JASON \ L. \ LIND - PRESIDENT/CHIEF \ ARCHITECT$

Jason L. Lind is a veteran software architect whose two-decades-long career centers on building production-grade artificial-intelligence systems with the Microsoft .NET ecosystem. He has designed and deployed AI-backed platforms that turn complex data into real-time, user-facing insight—from the **AI-driven Courseware.Coach** learning engine, built with Azure Bot Framework and Blazor, to **Programming.Team**, a full-stack resume-tailoring service whose ChatGPT-powered models analyze job descriptions and generate optimized candidate profiles. Earlier, as Lead Architect for United Airlines' Merchandising IT group, Jason introduced an AI-enabled pricing and recommendation API layer that contributed to a 30 percent quarter-over-quarter lift in ancillary-revenue per seat. These successes reflect deep hands-on expertise in C#, ASP.NET Core, SQL Server, Azure Functions, and modern DevOps pipelines—all applied to data-intensive, machine-learning workloads.

For the RailSight XR effort, Jason brings exactly the mix of skills needed to translate raw sensor or operational data into actionable augmented-reality overlays. His track record shows a consistent ability to: design cloud-to-edge inference pipelines that stay performant under tight resource budgets; integrate NLP, recommender, and computer-vision components into cohesive products; and roll out user-centric web or mobile front ends that surface AI insights without sacrificing reliability. By coupling this AI engineering background with rigorous test-driven development practices and decades of enterprise-grade architecture work, Jason is well positioned to lead the model-development, data-engineering, and software-integration tasks that underpin RailSight XR's real-time rail-inspection capability.

# JACK R. DRISCOLL – CHIEF ENGINEER

Jack Driscoll brings a complementary skill set that fortifies the communications backbone and edge-AI ambitions of the RailSight XR<sup>™</sup> program. As an RF and **wireless-network engineer**, he has designed and optimized Wi-Fi, LTE, and emerging 5G topologies for low-latency, high-reliability links—exactly the attributes our headset-to-edge-node architecture must deliver when railheads operate in spectrum-contested or infrastructure-poor environments. His deep knowledge of signal-propagation physics, interference-mitigation techniques, and network-security protocols ensures that RailSight XR's untethered sensor pod can maintain encrypted, jam-resilient connectivity while meeting Army cybersecurity requirements. Jack's experience translating complex propagation models into practical antenna and link-budget designs will help us hit the Phase I milestone for over-the-air demonstrations without costly iteration cycles.

Equally important, Jack's background in **programming convolutional neural networks for RF-signal identification** lets us extend our computer-vision pipeline with an RF-aware layer that can automatically detect and classify spectrum threats—alerting maintainers when GPS spoofing or hostile jamming might corrupt location or telemetry data. His electrical-engineering prowess in designing RF components and prototyping specialized antennas dovetails with our additive-manufacturing approach, enabling rapid integration of compact, low-power transceivers inside the Markforged-printed mount. Finally, Jack's systems-administration expertise—spanning Linux, Windows Server, and automated monitoring—strengthens our DevSecOps workflow and field-support plan, ensuring that deployed RailSight XR units can be patched, logged, and remotely diagnosed in accordance with Army sustainment doctrine. Together, these capabilities make Jack an essential contributor to both the technical execution and the commercialization roadmap of this SBIR effort.