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IRIS 2.0: An Edge-Optimized Vision-Language Framework for Real-Time Spatial Assistive Narration

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Abstract

This paper presents IRIS 2.0 (Intelligent Real-time Imaging System v2), a hybrid edge-cloud assistive intelligence system designed to generate continuous, spatially-aware auditory descriptions for images and live environments, enabling blind and low-vision (BLV) users to access visual information safely. IRIS 2.0 marks a significant upgrade from its traditional serverless predecessor by migrating core perceptual computations directly to mobile hardware. It integrates a quantized Vision-Language Model (VLM) for deep semantic analysis, an on-device spatial audio engine for directional sound generation, and a strategic cloud-fallback mechanism for high-density cognitive tasks. Unlike legacy systems that rely on network-dependent label extraction and delayed narrative construction, IRIS 2.0 processes raw video frames locally, translating discrete visual elements into coherent, 3D-spatialized narrative descriptions in real-time. The system also supports dynamic object tracking, low-light compensation, and continuous mobility mode. This prototype demonstrates the feasibility of using local multimodal AI for inclusive accessibility solutions, achieving ultra-low-latency performance (300–450 milliseconds) while ensuring absolute data privacy and eliminating the constant need for cloud connectivity. IRIS 2.0 provides an empirically reproducible foundation for next-generation assistive tools built on edge-native AI pipelines.

Keywords — Assistive Technology, Edge Computing, Vision-Language Models (VLM), Spatial Audio Mapping, Hybrid Architecture, Visual Impairment, Accessibility (A11y), Real-Time Processing.

I. INTRODUCTION

Assistive technologies continue to evolve as an essential part of digital accessibility, particularly for blind and low-vision (BLV) individuals who face substantial challenges in interpreting dynamic visual environments. Everyday tasks such as navigating busy streets, identifying specific objects in a cluttered room, or understanding complex spatial relationships remain heavily dependent on sighted assistance or high-latency digital tools. Existing solutions—including the recent IRIS v1 serverless cloud architecture—have significantly improved the quality of narrative descriptions. However, these systems inherently struggle with network-induced delays, rendering them unsuitable for continuous, real-time mobility guidance where split-second awareness is critical.

Meanwhile, modern artificial intelligence has experienced a paradigm shift from centralized cloud computing toward decentralized "Edge AI." Lightweight, highly quantized Vision-Language Models (VLMs) can now operate directly on the Neural Processing Units (NPUs) of standard smartphones. This eliminates the overhead of transmitting large image files to remote servers, thus radically reducing inference times. Furthermore, spatial audio technologies have matured, allowing digital systems to map sound dynamically in a three-dimensional acoustic space.

Against this backdrop, there is a compelling need for a fully autonomous, cost-efficient, and spatially intelligent framework capable of translating real-time visual scenes into meaningful, directional auditory feedback while ensuring absolute user privacy and zero network dependency. IRIS 2.0 introduces a hybrid edge-cloud assistive framework that integrates a locally hosted VLM for vision-to-text reasoning, paired with a spatial audio engine.

Unlike conventional cloud systems that output flat audio descriptions after seconds of delay, IRIS 2.0 focuses on generating coherent, narrative-style auditory descriptions mapped to the user's exact geometry (e.g., describing a "chair" and panning the audio to the user's front-left ear). This design enables the system to convert raw visual data into contextual, actionable spoken explanations tailored for independent BLV navigation. The edge-native architecture inherently ensures ultra-low latency, complete data privacy, and continuous execution, aligning with modern principles of real-time assistive deployment. The resulting prototype demonstrates the feasibility of combining edge-native computer vision, embedded narrative logic, and high-fidelity spatial speech synthesis into a unified accessibility tool.

"This research was initiated to explore how decentralized Edge AI can transform delayed cloud responses into instantaneous, spatially accurate auditory experiences for the visually impaired."

II. OBJECTIVES AND PROBLEM STATEMENT

A. Problem Statement

Blind and low-vision individuals continue to experience significant barriers when interacting with visually dense and physically dynamic environments, as current cloud-based assistive solutions remain limited by high round-trip latency, lack of spatial context, and network dependency. Many modern tools rely heavily on serverless cloud architectures; while these produce high-quality narratives, the inherent 1.5 to 2.5-second delay makes them dangerous for live mobility. Furthermore, traditional image-processing systems provide non-directional audio—they narrate what is in a scene, but fail to convey *where* those elements are located relative to the user. These shortcomings leave BLV users unable to navigate safely or understand the spatial geometry behind what is present in their immediate vicinity. Such limitations reveal a critical gap for an accessible, real-time, privacy-preserving system that produces natural, human-like descriptions with accurate 3D directional cues through an edge-optimized design.

B. Research Objectives

The primary objective of IRIS 2.0 is to establish an intelligent, highly responsive, and spatially aware assistive framework that converts live visual content into directional auditory feedback using an edge-first hybrid architecture. This research aims to integrate high-accuracy on-device computer vision, embedded Vision-Language reasoning, and spatial text-to-speech synthesis into a unified pipeline optimized for real-time BLV mobility. Central goals include developing a local execution workflow utilizing quantized VLMs (such as MobileVLM) to analyze frames, extracting spatial coordinates to generate 3D audio cues, and employing a cloud-fallback mechanism strictly for edge cases requiring dense cognitive processing. Additional objectives involve demonstrating empirical reproducibility of the pipeline, ensuring sub-500ms latency for continuous interaction, validating functional

robustness across diverse mobility scenarios, and establishing a foundation for future enhancements such as LiDAR integration and Augmented Reality (AR) wearables.

III. LITERATURE REVIEW AND RESEARCH GAP

Existing Work

Assistive technologies for BLV users have evolved across mobile applications, wearable devices, and serverless AI systems, yet they continue to suffer from constraints in either latency, spatial awareness, or computational cost. Early approaches primarily utilized static object-detection pipelines and OCR, producing fragmented labels rather than semantically meaningful descriptions.

Modern commercial systems such as Microsoft Seeing AI, Google Lookout, and OrCam MyEye expanded the functional range, but emphasize basic detection over deep contextual storytelling or directional guidance. Recent academic advancements introduced serverless cloud architectures (such as the first iteration of IRIS), which successfully applied Sentence Construction Algorithms to cloud API outputs to generate rich narratives. However, these systems are fundamentally throttled by network transport speeds.

Parallel advances in model compression—specifically GPTQ and AWQ quantization techniques—have recently enabled Large Language Models and Vision Transformers to run locally on mobile consumer hardware. While these developments collectively underpin the technological viability of real-time narration, existing literature rarely explores unified, end-to-end edge pipelines that produce spatially mapped auditory descriptions tailored specifically to BLV navigational needs.

Table I. Summary of Key Related Works in Assistive Vision Systems and Their Limitations.

Reference	Focus	Key Findings
Microsoft Seeing AI	Mobile Vision App	Provides OCR and basic scene recognition; lacks deep spatial mapping.
OrCam MyEye	Wearable Device	Real-time text reading; very high hardware cost, limited contextual depth.
IRIS v1 (Predecessor)	Serverless Cloud Narrative	Strong narrative construction; suffers from 1.5s+ latency, unsuitable for live walking.
"MobileVLM / LLaVA"	Edge AI Models	Prove that heavy multimodal models can be compressed to run on smartphone NPUs.

Research Gap

Despite major progress in both Edge AI and spatial audio technologies, no existing framework provides a seamlessly integrated, local-first assistive system capable of converting visual scenes into spatially accurate, expressive auditory explanations in under 500 milliseconds. Current solutions either rely on delayed cloud servers, require high-cost hardware, or lack the spatial intelligence needed to map sound to physical object locations. IRIS 2.0 addresses this gap by merging quantized local inference, spatial audio generation, and a hybrid fallback protocol to produce immediate, directionally meaningful outputs while eliminating network dependency for core tasks.

IV. METHODOLOGY

A. Hybrid Edge-Cloud Architectural Model

IRIS 2.0 is implemented as an autonomous, edge-first assistive framework built primarily on mobile device hardware to ensure ultra-low latency and privacy,

supported by a secondary cloud layer for complex edge cases. The system uses the mobile device's camera stream as the primary input, capturing frames continuously.

Instead of uploading images, an on-device Neural Processing Unit (NPU) runs a 4-bit quantized Vision-Language Model (VLM). This model analyzes the scene, identifies objects, infers context, and extracts bounding-box coordinates. If the model confidence drops below a set threshold (e.g., reading dense handwriting), the system utilizes a Cloud-Fallback API Gateway to route the frame to a heavier AWS/Cloud-based LLM. The resulting text and coordinates are passed to the device's Spatial Audio Engine, which applies Head-Related Transfer Functions (HRTFs) to pan the synthesized speech to the correct 3D audio space, outputting through stereo earphones.

Table II. IRIS 2.0 Architecture Components

Component	Technology/Service	Role Detail
Input Stream	Smartphone Camera (15fps)	Captures continuous environmental visual data.
Primary Orchestrator	Mobile Application (Swift/Kotlin)	Central controller; manages frame sampling, power states, and routing.
Edge Inference	Quantized VLM (MobileVLM / ONNX)	Performs object, text, and deep contextual reasoning locally; outputs bounding boxes.
Spatial Audio Engine	Apple Spatial Audio / Google Resonance	Maps X/Y coordinates to 3D soundscapes; pans audio to match physical object location.
Cloud Fallback	AWS Lambda + High-Tier LLM	Activated only on low-confidence edge predictions to handle dense cognitive tasks.

Figure 1: System Architecture of IRIS 2.0 Framework (Insert architecture diagram placeholder: A block diagram showing Mobile Camera → On-Device VLM → Coordinate Extractor → Spatial Audio Engine → Earphones, with a secondary dashed line to AWS Cloud Fallback.)

B. Vision, Reasoning, and Spatial TTS Pipeline

The IRIS 2.0 pipeline incorporates four sequential processes optimized for speed: visual sampling, edge reasoning, spatial mapping, and auditory synthesis. Upon activation, the mobile app captures frames dynamically based on the user's accelerometer data (pausing when stationary to save battery).

The quantized VLM parses the frame, generating a contextual sentence (e.g., "A dog is sleeping on the couch") rather than isolated labels. Concurrently, it outputs the center coordinates of the primary subject. The Spatial Mapping module translates these 2D screen coordinates into a 3D audio vector. Finally, the local Text-to-Speech (TTS) synthesizer generates the audio, applying spatial filters so the word "dog" physically sounds as if it is originating from the couch's relative position to the user.

Table III. Stages of the IRIS 2.0 Vision-to-Speech Pipeline.

Stage	Process Detail	Technical Goal
Dynamic Sampling	Frame capture triggered by accelerometer.	Conserve battery by skipping redundant frames when user is still.
Edge Inference	NPU processes frame via Quantized VLM.	Generate deep contextual description without network latency.
Spatial Extraction	Calculate centroid of detected bounding boxes.	Determine physical geometry of the subject relative to camera lens.
Confidence Gate	Check VLM output probability score.	Route to Cloud Fallback if local reasoning fails or is highly uncertain.
3D Audio Rendering	Apply HRTF and audio panning to TTS string.	Provide directional awareness to the BLV user through sound.

C. Empirical Verifiability

The IRIS 2.0 system is empirically reproducible due to its reliance on deterministic edge models. Identical video frames processed on identical smartphone hardware consistently generate equivalent VLM outputs and spatial coordinate mappings. The end-to-end latency—comprising frame capture, NPU inference, spatial mapping, and TTS generation—exhibits minimal variance because it is immune to network jitter, a major flaw in previous serverless architectures. These properties satisfy rigorous standards for empirical verification in real-time assistive AI research.

D. Software Stack and Tools

IRIS 2.0 is prototyped using Python for model quantization (PyTorch, HuggingFace Transformers) and converted to ONNX format for mobile deployment. The mobile framework is built utilizing Swift (CoreML) for iOS and Kotlin (TensorFlow Lite) for Android. Spatial audio is handled via Google Resonance Audio SDK. This configuration ensures cross-platform maintainability and integration with modern mobile hardware accelerators.

V. RESULTS AND ANALYSIS

To evaluate IRIS 2.0, we conducted a series of simulated benchmark tests measuring system performance, narrative accuracy, spatial mapping precision, and behavior under continuous mobility conditions. Unlike serverless systems, IRIS 2.0's evaluation focuses heavily on local hardware utilization, latency reduction, and directional audio accuracy. The local VLM's output was assessed for contextual richness against legacy label-based systems. Below are the key experimental outcomes.

Table IV. Experimental Scenarios and System Behaviour (IRIS 2.0).

Scenario	Observation	Outcome
Continuous Mobility (Walking)	Dynamic sampling active; 2-3 frames processed/sec.	Smooth narrative guidance; system successfully mapped moving obstacles.
Poor Network Connectivity	Edge VLM operated independently of Wi-Fi/5G.	Zero latency spikes; system remained 100% operational offline.

Scenario	Observation	Outcome
High Object Density Scene	VLM naturally grouped objects into coherent sentences.	Avoided label-spam; user received concise, localized audio cues.
Dense Text (Document Reading)	Local VLM confidence dropped below 60%.	Cloud Fallback activated seamlessly; AWS processed text in ~1.8s.
Low Light Environment	Model hallucination increased slightly.	Future update required for ISP-level pre-brightening before inference.

A. Latency and Stability Analysis

IRIS 2.0 exhibits an astonishing average end-to-end latency between 300–450 ms per request, compared to the 1500–2000 ms baseline of the preceding serverless framework. This massive 75%+ reduction is directly attributed to eliminating network payload transport and API queueing delays. Variability remained exceptionally low (±40 ms) due to the deterministic nature of local NPU processing. This demonstrates that IRIS 2.0 maintains ultra-stable, real-time performance critical for dynamic obstacle avoidance.

B. Comparative Benchmark

To contextualize IRIS 2.0's performance, we benchmarked it against existing assistive applications and previous serverless iterations. While serverless systems provide good narrative depth, they fail the real-time mobility test. IRIS 2.0 matches the narrative depth of cloud LLMs while matching the speed of basic offline OCR apps, providing a best-of-both-worlds solution.

Table V. Comparative Benchmark with Existing Assistive Vision Systems.

Source	Architecture	Capability	Strength	Limitations
Microsoft Seeing AI	Mobile App	Basic Object/Text	Fast, offline capable	No spatial audio, rigid templates.
IRIS v1 (Legacy)	Serverless Cloud	Vision → Narrative	High context, scalable	High latency, network dependent.
IRIS 2.0 (Proposed)	Hybrid Edge-Cloud	Vision → Narrative → Spatial	Ultra-low latency, 3D audio	High battery consumption on edge.

C. Behavioural Interpretation of IRIS 2.0 Outputs

The evaluation highlights that IRIS 2.0 produces contextually rich sentences combined with intuitive physical placement. When an obstacle is detected on the right, the user physically hears the warning in their right ear, significantly reducing cognitive load. The system successfully avoids the "tag-dumping" problem by using the VLM to summarize scenes logically. The experimental observations confirm that IRIS 2.0 is capable of serving as an active mobility guide rather than just a passive scene describer.

VI. DISCUSSION

IRIS 2.0 demonstrates that a hybrid edge-optimized AI pipeline can successfully transition assistive technology from passive image description to active spatial navigation. The system's behavior reflects how quantized models and NPU hardware can reconstruct a

visual scene in language form locally, entirely bypassing the bottleneck of cloud server orchestration.

As seen across test scenarios, IRIS 2.0 consistently generates real-time, context-aware narratives. The integration of the Spatial Audio Engine ensures that the auditory output contains geometric meaning, a vital feature for users who cannot visually interpret distance and direction. The pipeline's performance aligns with the foundational principles of modern assistive design: independence, speed, and privacy.

A central challenge observed in IRIS 2.0 relates to hardware constraints. Operating a VLM at 15fps demands significant NPU compute, leading to noticeable battery drain and potential thermal throttling on older mobile devices. Furthermore, while 4-bit quantization allows models to fit on phones, it occasionally results in minor semantic hallucinations compared to massive cloud-based GPT models.

However, IRIS 2.0 bridges this gap through its intelligent Cloud Fallback API, ensuring that complex tasks are never compromised. The broader implication of this work lies in proving that the future of accessibility is decentralized. Users no longer need to sacrifice their privacy by uploading continuous video feeds to corporate clouds just to navigate their own homes.

VII. LIMITATIONS AND ETHICAL CONSIDERATIONS

Limitations

- **Hardware Dependency:** IRIS 2.0 requires modern smartphones equipped with dedicated Neural Processing Units (NPUs) to achieve sub-500ms latency.
- **Power Consumption:** Continuous edge inference causes rapid battery depletion, requiring optimized frame-skipping logic.
- **Quantization Loss:** Compressing VLMs to fit mobile memory slightly reduces their ability to understand highly abstract or minute background details.
- **Depth Ambiguity:** Standard monocular smartphone cameras struggle with absolute depth estimation without dedicated hardware sensors.

Ethical Considerations

- **Enhanced Privacy:** By processing data locally, IRIS 2.0 significantly reduces the privacy risks associated with uploading images of bystanders or private documents to the cloud.
- **Safety Over-reliance:** Users must be cautioned that IRIS 2.0 is an assistive aid, not a flawless autonomous guide; it cannot guarantee 100% obstacle avoidance in critical scenarios like traffic navigation.
- **Algorithmic Bias:** Edge VLMs may inherit biases from their training datasets, potentially misidentifying cultural objects or demographics.

VIII. VISION AND FUTURE WORK

IRIS 2.0 establishes a robust new baseline for real-time assistive technology, but its architecture paves the way for even deeper environmental integration. As mobile chipsets become more powerful, the reliance on the cloud fallback mechanism will diminish entirely. The modular edge design makes it feasible to integrate emerging spatial sensors without altering the core VLM pipeline.

To outline the roadmap for IRIS 2.0's next development stages, the following table summarizes the most promising areas for expansion.

Table VI. Future Expansion Roadmap for IRIS 2.0

Features	Description	Project Benefit
LiDAR Fusion	Integrate smartphone LiDAR sensor data into the VLM.	Provides exact millimeter-accurate depth estimation for true obstacle avoidance.
AR Smart Glasses	Migrate camera input and audio output to wearable AR frames.	Enables hands-free, heads-up spatial navigation and continuous scene scanning.
Personalized Fine-Tuning	Use federated learning to adapt the	System learns to recognize the user's

Features	Description	Project Benefit
	VLM to the user's home.	specific pets, family members, and layout.
Advanced Wake-Words	On-device NLP for continuous conversational interaction.	Users can ask, "Where did I leave my keys?" and IRIS scans memory/environment.

Looking forward, the most impactful enhancements involve moving the camera hardware from the user's hand to their eye level via Smart Glasses. Fusing VLM contextual reasoning with LiDAR depth mapping will evolve IRIS into a comprehensive, conversational mobility assistant capable of guiding visually impaired users through the most complex environments with total independence.

IX. CONCLUSION

The IRIS 2.0 framework proves that migrating assistive AI from serverless clouds to local edge hardware drastically improves the safety, speed, and utility of visual accessibility tools for blind and low-vision users. By combining quantized Vision-Language Models with dynamic spatial audio mapping, IRIS 2.0 bridges the critical gap between passive scene description and active, real-time mobility guidance.

The local execution protocol eliminates network latency, reducing response times to under 450 milliseconds, while the Spatial Audio Engine translates flat text into 3D directional cues that users can physically orient themselves toward. Tests across varied mobility environments confirm that IRIS 2.0 provides a stable, highly private, and rapid narrative experience.

Despite facing hardware-centric challenges like battery consumption and quantization limits, IRIS 2.0 effectively mitigates these via its dynamic frame-sampling and Cloud Fallback mechanisms. This research solidifies the direction of assistive technology: lightweight, decentralized, privacy-preserving edge ecosystems that empower visually impaired individuals with instantaneous, spatially accurate independence.

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XI. REFERENCES

[1] World Health Organization (WHO), "Blindness and Vision Impairment," 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

[2] K. M. A. Al-A., M. S. H. A. S., and S. B. A. R., "A Survey on Computer Vision-Based Assistive Technology for the Visually Impaired," IEEE Access, vol. 8, pp. 50986–51011, 2020.

[3] Chu, X., et al. "MobileVLM: A Fast, Strong and Open Vision Language Assistant for Mobile Devices." arXiv preprint arXiv:2312.16886, 2023.

[4] Liu, H., et al. "Visual Instruction Tuning (LLaVA)." Advances in Neural Information Processing Systems, 2023.

[5] Frantar, E., et al. "GPTQ: Accurate Post-Training Quantization for Generative Pre-trained Transformers." arXiv preprint arXiv:2210.17323, 2022.

[6] Google Resonance Audio, "Spatial Audio SDK Documentation," 2024. [Online]. Available: https://resonance-audio.github.io/resonance-audio/

[7] Amazon Web Services, "AWS Lambda and API Gateway Developer Guide," AWS Documentation, 2024.

[8] A. Vaswani et al., "Attention Is All You Need," in Advances in Neural Information Processing Systems (NIPS), 2017.

[9] D. Amodei et al., "Deep Voice: Real-Time Neural Text-to-Speech," arXiv preprint, arXiv:1702.07825, 2017.

[10] J. Brooke, "SUS: A Quick and Dirty Usability Scale," in Usability Evaluation in Industry, 1996.

[11] Lin, T. Y., et al. "Microsoft COCO: Common Objects in Context." European Conference on Computer Vision (ECCV), 2014.