NeuroLens: A Cognitive-aware Assistive Navigation Framework for the Visually Impaired using EEG and 3D Spatial Perception

W.M.A.J Weerabahu
Department of Software Engineering & Computer Security, Faculty of Computing, NSBM Green University, Sri Lanka
wmajanodani@students.nsbm.ac.lk

Diluka Wijesinghe
Department of Software Engineering & Computer Security, Faculty of Computing, NSBM Green University, Sri Lanka
diluka.w@nsbm.ac.lk

***Abstract*— Globally, over 250 million people live with moderate to severe visual impairments, facing significant barriers to safe and independent navigation. While assistive tools such as canes, guide dogs, and smartphone-based apps exist, these solutions often require physical interaction, lack environmental awareness, and fail to adapt to user intent or cognitive state. This conceptual research proposes a high-level architecture for "NeuroLens," a brain-computer interface (BCI)-driven navigation framework that integrates non-invasive EEG signals with real-time 3D spatial perception using depth cameras. The goal is to enhance hands-free mobility for visually impaired users by inferring navigation intent and delivering contextual feedback via audio and haptic channels. Unlike existing AR or BCI-based tools, NeuroLens introduces a dual-input decision mechanism and continuous real-time deviation monitoring through an FSM controller. Although no prototype has been implemented, the system design is grounded in prior literature and optimized for mobile platforms. Future work will focus on prototype development, performance benchmarking, and real-world usability evaluation to validate the framework's feasibility and effectiveness.**

Keywords- assistive navigation design , Brain-Computer Interface, Electroencephalography, intent recognition,

I. INTRODUCTION

Navigation in complex environments remains one of the most persistent challenges for individuals who are blind or visually impaired. According to the World Health Organization, more than 250 million people worldwide experience moderate-to-severe visual impairment [4]. These individuals often rely on traditional mobility aids such as white canes and guide dogs, which, while effective for basic obstacle avoidance, offer little contextual awareness and require continuous physical engagement. Camera-based smartphone applications offer enhanced perception, but their dependence on hand-based or voice-based interaction renders them impractical in crowded, noisy, or socially sensitive environments [3], [5].

Recent technological advancements in two independent fields—brain-computer interfaces (BCIs) and augmented reality (AR)—present new possibilities for intelligent assistive systems. BCIs using non-invasive electroencephalography (EEG) have demonstrated the ability to decode motor imagery, attention, and even emotional states in real time without requiring physical interaction [8], [14], [29]. Meanwhile, AR technologies leveraging stereo vision and edge-based machine learning (e.g., Luxonis OAK-D Lite) provide real-time spatial localization, object recognition, and scene understanding suitable for mobile use [19], [22].

However, despite significant progress in both domains, existing solutions remain siloed. Most assistive technologies are either perception-based (e.g., obstacle detection via camera) or cognition-based (e.g., EEG-driven control systems), but rarely integrate both. This lack of integration prevents current tools from providing proactive, personalized guidance that adapts not only to the environment but also to the user's cognitive state and intent. No current system combines EEG-based intent decoding with spatially aware AR in a wearable, mobile form factor for autonomous navigation. This forms a key research gap.

In response, this study presents a conceptual framework for NeuroLens—a mobile, brain-driven assistive navigation system that merges real-time EEG-based user intent recognition with 3D scene understanding using wearable AR cameras. The system design includes multimodal feedback mechanisms (audio and haptics), a finite-state controller for decision logic, and optional emotion-aware modules. The primary objective is to enable safe, hands-free navigation by interpreting the user's intent and providing context-aware feedback, all while minimizing user effort and interaction. Although no prototype has been implemented, the proposed architecture is grounded in validated algorithms and designed for practical mobile deployment, serving as a blueprint for future development and evaluation.

II. LITERATURE REVIEW

The development of assistive navigation technologies for visually impaired individuals has evolved across multiple technological domains, with significant advances in brain-computer interfaces (BCIs), augmented reality (AR), and computer vision systems. However, existing research has predominantly focused on isolated implementations rather than integrated multimodal approaches, creating opportunities for more comprehensive solutions.

A. Brain-Computer Interface Systems for Navigation

EEG-based BCI systems have demonstrated considerable potential for decoding user intent through various neural signal patterns. Motor imagery paradigms, as extensively reviewed by Pfurtscheller and Neuper [29], provide robust foundations for intention detection in assistive applications. Li et al. [1] developed an adaptive steady-state visual evoked potential (SSVEP) recognition framework for AR-based

control, demonstrating the feasibility of real-time neural signal processing for navigation commands. Furthermore, Zhou et al. [31] explored emotion detection capabilities within BCI systems, revealing opportunities for behavioral modulation based on cognitive state assessment.

Despite these advances, current BCI-based navigation systems face significant limitations in environmental awareness. Most implementations rely exclusively on neural signals without incorporating spatial context, resulting in navigation assistance that lacks real-world adaptability. The comprehensive review by de Oliveira et al. [2] specifically identified the absence of emotion-aware, mobile EEG-AR integrations as a critical gap in current assistive technology research.

B. Computer Vision and Augmented Reality Applications

Parallel developments in computer vision have enabled sophisticated environmental perception capabilities for assistive navigation. Real-time object detection and three-dimensional mapping technologies have matured to support practical deployment scenarios. The Luxonis OAK-D Lite stereo vision platform exemplifies current edge computing capabilities, supporting models such as YOLOv8 [18] for real-time inference on mobile devices.

Smartphone-based navigation systems have shown practical viability, with Michele et al. [26] demonstrating effective obstacle recognition using visual markers for indoor navigation. Simultaneous Localization and Mapping (SLAM) frameworks, particularly ORB-SLAM3, have been extensively reviewed by Goyal and Banga [27] for real-time localization in assistive contexts, establishing the technical foundation for accurate spatial awareness in dynamic environments.

However, existing AR-based assistive technologies typically require manual command input or external triggers, limiting their effectiveness for users requiring hands-free operation. These systems lack the ability to proactively respond to user intent, creating barriers to seamless navigation experiences.

C. Integration Challenges and Research Gaps

Contemporary assistive technology reviews [3], [4] consistently highlight the fragmented nature of current solutions and emphasize the critical need for systems that adapt to users' cognitive and emotional states. The fundamental limitation across existing approaches is their reliance on single-modality input mechanisms. BCI systems demonstrate strong intent recognition capabilities but lack environmental context, while computer vision systems provide detailed spatial awareness without understanding user intentions or cognitive state.

Recent systematic reviews have identified several key gaps: (1) the absence of real-time integration between neural signal processing and environmental perception, (2) limited adaptation to user cognitive load and emotional state, and (3) insufficient consideration of mobile deployment constraints in unified BCI-AR architectures. These limitations create significant barriers to developing truly autonomous and user-centric navigation assistance.

D. Toward Integrated Multimodal Approaches

The convergence of advances in portable EEG systems, edge computing capabilities, and real-time computer vision processing creates unprecedented opportunities for integrated assistive navigation frameworks. NeuroLens addresses the identified research gaps by proposing a unified architecture that combines intent recognition through EEG signal processing with real-time spatial mapping and context-driven feedback mechanisms.

This integrated approach represents a paradigm shift from isolated technological implementations toward holistic user-centric design. By consolidating recent developments in BCI signal processing, computer vision algorithms, and multimodal feedback systems, the proposed framework enables cognitively adaptive, hands-free navigation that maintains continuous environmental awareness. The modular architecture ensures extensibility for future technological advances while addressing immediate practical deployment requirements for real-world assistive applications.

III. METHODOLGY

The proposed NeuroLens framework is a novel, mobile-centric assistive navigation system designed specifically for visually impaired users. It integrates cognitive neuroscience, wearable computing, and spatial artificial intelligence into a cohesive, real-time platform. The system combines EEG-based intent recognition with advanced visual perception and multimodal feedback to enable intelligent, context-aware navigation without requiring explicit user interaction.

A. EEG Data Acquisition and Processing

NeuroLens employs a 16-channel OpenBCI Cyton board for acquiring EEG signals. Electrodes follow the international 10–20 system with a focus on the motor cortex (C3, C4) and visual cortex (O1, O2) to capture motor imagery and attentional signals. The EEG headset transmits data wirelessly via Bluetooth to a mobile processing unit.

The raw EEG data undergoes a preprocessing pipeline including:

- Band-pass filtering (0.5–45 Hz) to isolate relevant brain rhythms
- Notch filtering (50/60 Hz) to remove power line noise
- Independent Component Analysis (ICA) to eliminate ocular and muscle artifacts

After artifact removal, data are normalized and segmented for feature extraction.

B. Feature Extraction and Classification

NeuroLens extracts spectral and spatial features using FFT-based band-power analysis and Common Spatial Patterns (CSP). The classification module supports two operational modes:

- Lightweight mode: Uses Linear Discriminant Analysis (LDA) or Support Vector Machine (SVM) for real-time, low-latency mobile inference
- High-performance mode: Employs a hybrid Convolutional Neural Network (CNN) and Long

Short-Term Memory (LSTM) model for offline or edge computing scenarios

This dual approach balances efficiency and accuracy depending on deployment constraints.

C. AR Perception and 3D Mapping

Visual input is acquired via a wearable Luxonis OAK-D Lite stereo camera integrated into AR glasses. Object and obstacle detection are handled by the optimized YOLOv8 model, while real-time 3D localization and mapping use ORB-SLAM3, supporting map reuse and continuous spatial awareness. The system synchronizes spatial mesh data and object labels with EEG-inferred user intent for enriched environmental understanding.

D. Decision Logic Integration

At the core of NeuroLens is a Finite State Machine (FSM) controller that fuses EEG-derived commands and AR context data. This rule-based controller translates cognitive intentions and environmental conditions into a time-sensitive action queue, ensuring transparent, explainable, and safe decision-making suitable for assistive applications.

E. Multimodal Feedback System

NeuroLens provides intuitive guidance through:

- Auditory feedback: Offline text-to-speech (TTS) using engines like Coqui to deliver scene descriptions and alerts
- Haptic feedback: Directional vibration motors embedded in a wearable wristband provide tactile cues for navigation direction

This combination is designed for minimal disruption, maintaining situational awareness and reducing cognitive load.

F. Mobile-Centric Lightweight Architecture

Unlike traditional assistive systems dependent on desktop computing or cloud processing, NeuroLens operates efficiently on smartphones by leveraging lightweight EEG classifiers and optimized computer vision models. This approach ensures low latency, energy efficiency, and field usability in real-world settings.

G. Proposed Future Enhancements

A planned extension involves real-time emotion recognition from EEG signals to detect user states such as stress or confusion. The system would then adapt feedback intensity, pause navigation, or seek user confirmation to enhance safety and comfort.

H. System Integration

The overall architecture (illustrated in Fig 1) demonstrates real-time interaction among EEG acquisition, AR perception, classification modules, FSM decision logic, and multimodal feedback within the mobile app framework, enabling a seamless user experience.

I. Ethical and Accessibility Considerations

NeuroLens adheres to stringent ethical guidelines, including:

- Ensuring user privacy by avoiding cloud storage without explicit consent
- Providing clear informed consent before data collection and system use
- Tuning feedback mechanisms to avoid intrusiveness and preserve environmental sound awareness
- Designing for inclusivity and adaptability to varying levels of visual impairment
- Prioritizing explainability and safety through transparent FSM-based control

J. Innovation Summary

NeuroLens marks a paradigm shift in assistive navigation by integrating dual-channel input fusion (cognitive EEG and spatial vision), a lightweight mobile architecture, a real-time closed-loop feedback system, and an intent-driven FSM controller. Its low-cost, scalable design leverages open-source hardware and software to make advanced assistive technology accessible to diverse populations, promoting autonomous and intelligent navigation for visually impaired users.

IV. RESULTS AND DISCUSSIONS

Although NeuroLens remains a conceptual framework, this section outlines theoretical feasibility, expected performance, and comparative advantages based on current literature and the system design.

A. Feasibility Analysis The system is designed to run entirely on mobile hardware with low-power components:

- EEG processing latency (OpenBCI + LDA/SVM): <10 ms for binary classification
- YOLOv8 object detection on mobile SoCs: ~30 FPS on Snapdragon 8 Gen 2-class chipsets
- ORB-SLAM3 mapping latency: ~15–30 ms/frame with visual-inertial input
- Total system loop latency (EEG + vision + feedback): Estimated <250 ms, which is suitable for real-time guidance

B. Component Validation (Literature-Based)

- EEG classification accuracy (LDA/CSP): Reported ~75–90% accuracy on motor imagery tasks [14], [15
- YOLOv8 detection performance: Precision of ~80% and recall ~68% in obstacle-rich outdoor datasets [19]
- ORB-SLAM3 localization: Centimeter-level accuracy in dynamic environments [20].

C. Simulation Plan (Future Work)

- MATLAB or Unity3D simulation of indoor navigation with EEG command injection and YOLO-based obstacle streaming
- Evaluation of latency budget and feedback responsiveness

- Prototype testing with mock EEG and 3D camera data for FSM sequence control

D. Limitations and Open Issues

- No implementation currently exists; all performance data are drawn from literature benchmarks
- Real-world EEG signals are noisy and subject-specific, requiring user calibration
- Emotion recognition via EEG remains an emerging area with limited robustness.

TABLE6:COMPARISON OF NAVIGATION TECHNOLOGIES FOR THE VISUALLY

System	Input Type	Feedback	Autonomous	Intent Recognition	Real-Time Spatial Awareness
White Cane	Tactile	None	✗	✗	✗
Smartphone App	Camera/Voice	Audio	✗	Voice	Partial
BCI Navigation (prior art)	EEG	Audio	✗	✓	✗
AR Glasses (YOLO-based)	Camera	Audio	✗	✗	✓
NeuroLens (Proposed)	EEG + AR	Audio + Haptics	✓	✓	✓

E. Ethical and Practical Considerations for Deployment

- User privacy (e.g., on-device EEG analysis).
- Safety overrides in high-noise or urban environments.
- Usability for diverse levels of visual impairment and cognitive ability.

V. FEASIBILITY ANALYSIS

This section assesses the theoretical viability of the proposed NeuroLens framework, based on known capabilities of its components and existing benchmarks from prior literature.

I. A. EEG-BASED INTENT RECOGNITION FEASIBILITY

NeuroLens employs lightweight classifiers (LDA/SVM) and optionally CNN+LSTM models for real-time EEG signal classification. Prior studies such as [14], [15], and [16] have shown:

- >80% accuracy in binary EEG intent classification with as few as 8–16 channels.
- <200 ms latency for signal acquisition to decision, using OpenBCI hardware and optimized algorithms [11], [15].
- These results indicate that low-latency intent recognition can be feasibly achieved on mobile-class hardware.

II. B. OBJECT DETECTION AND 3D PERCEPTION

Using the OAK-D Lite stereo depth camera and YOLOv8 on the onboard Myriad X VPU, prior work [18], [19] reports:

- ≥30 FPS object detection
- ~80% precision in obstacle-rich environments
- Depth estimation with <2 cm error in real-time
- This supports robust AR scene understanding suitable for wearable deployment.

A. C. Spatial Mapping and Localization

The integration of ORB-SLAM3 supports:

- Centimeter-level real-time localization using monocular/stereo vision [20]
- Loop closure and map reuse, critical for dynamic urban environments
- These characteristics ensure stable scene anchoring and dynamic path correction.

B. D. Latency and Computational Efficiency

Assuming edge computing or smartphone deployment:

- EEG preprocessing and classification: ~50–100 ms
- Visual inference (YOLOv8): ~25–40 ms
- Total perception-to-feedback loop latency: <200 ms

This is within acceptable bounds for real-time assistive applications.

VI. ETHICAL AND PRIVACY CONSIDERATIONS

Deployment of wearable, cognitive-aware navigation systems involves several ethical dimensions that must be carefully addressed:

- User Consent: Users must give informed consent for EEG signal collection and emotional state monitoring. Transparent communication about data use is essential.
- Data Privacy: All EEG and camera data should be processed on-device or in a secure, encrypted form if cloud storage is necessary. Personal identifiers must never be stored or transmitted without encryption.
- Safety in Public Environments: Devices like AR glasses and EEG headsets must be ergonomically designed to avoid accidents or distractions, and must comply with health and safety regulations [21], [24].
- User Trust: Haptic and audio feedback must be intuitive and customizable. Misclassification or over-alerting could erode user confidence and reduce adoption.
- Future human subject testing will be guided by institutional ethical board approval processes and adapted protocols from prior work on BCI and assistive navigation studies [2], [10], [23].

VII. IMPLEMENTATION CONSIDERATIONS AND LIMITATIONS

A. Implementation Considerations

The NeuroLens framework has been designed with a focus on deployability on mobile and wearable platforms, aiming to deliver real-time, context-aware assistive navigation for visually impaired users.

Key implementation features include a mobile and lightweight architecture that utilizes optimized EEG classifiers and compact computer vision models to ensure efficient operation on smartphones and wearable devices, thereby minimizing latency and power consumption. The system supports real-time data processing using a 16-channel OpenBCI Cyton board for EEG acquisition, incorporating preprocessing techniques such as band-pass and notch filtering, artifact removal through independent component analysis (ICA), and feature extraction for intent classification.

Furthermore, multimodal feedback mechanisms are integrated, combining auditory (text-to-speech) and haptic (directional vibration) channels to deliver guidance without interrupting user awareness. A Finite State Machine (FSM)-based decision logic fuses EEG-derived intent with augmented reality (AR) spatial context, enabling safe and context-aware navigation. Finally, the system demonstrates modularity and extensibility, allowing seamless integration of future enhancements such as emotion recognition while maintaining architectural flexibility for continuous development.

B. Limitations

Despite its promising design, several limitations are recognized. Absence of Physical Prototype: The framework is currently conceptual; no physical prototype has been constructed or tested. Subject-Specific Calibration: EEG signal variability among users necessitates individualized calibration for optimal performance.

Emotion Recognition Robustness: EEG-based emotion detection remains an emerging field, with current models lacking the robustness required for universal application. Ethical and Safety Concerns: Deployment in public environments introduces privacy, safety, and usability challenges that require careful management. Computational Constraints: Although optimized for mobile hardware, real-world performance may be constrained by device limitations and environmental noise.

VIII. RESULTS AND DISSCUSION

A. Results

A literature-based feasibility analysis was conducted to evaluate the potential performance of the proposed NeuroLens framework. In terms of EEG classification, prior studies reported intent recognition accuracy rates ranging from 75% to 90% using Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM) on motor imagery tasks. For object detection, the YOLOv8 implementation on the OAK-D Lite camera achieved approximately 80% precision and 68% recall in obstacle-rich environments. The ORB-SLAM3 algorithm provided centimeter-level localization accuracy, demonstrating suitability for precise navigation assistance. Furthermore, the total system loop latency was estimated to be less than 250 milliseconds, indicating the feasibility of supporting real-time guidance. A simulation plan was established to further validate system performance, with future work to include MATLAB or Unity3D simulations for navigation, EEG command injection, and feedback responsiveness.

B. Discussion

The NeuroLens framework addresses a critical gap in assistive navigation technologies by integrating EEG-based intent recognition with AR-based spatial awareness. This dual-input approach enables hands-free, context-aware, and cognitively adaptive guidance for visually impaired users.

While current performance metrics are based on established literature, real-world deployment may introduce

additional challenges related to EEG and visual data quality. The framework's modular and scalable design positions it for broad adoption, provided that user trust, privacy, and safety are prioritized in ongoing development.

IX. CONCLUSION

This paper presents the conceptual framework for NeuroLens, a brain-driven assistive navigation system for visually impaired individuals. The primary contribution is the integration of real-time EEG-based intent recognition with spatial scene understanding, delivering a theoretically grounded model that bridges the gap between perception- and cognition-based assistive technologies.

Key contributions include the design of a lightweight mobile architecture combining OpenBCI-based EEG acquisition, dual-mode classification (LDA/SVM, CNN+LSTM), YOLOv8 for obstacle detection, ORB-SLAM3 for spatial mapping, and a finite-state controller for decision logic. The proposed multimodal feedback strategy comprising haptic and audio channels prioritizes low latency and minimal cognitive load. Insights from the architectural and literature-based analysis suggest EEG-based intent recognition with up to 90% classification accuracy. Real-time AR processing at 30+ FPS on mobile SoCs and End-to-end latency below 250 ms. Despite the promising theoretical feasibility, this system remains unimplemented. There are significant challenges related to EEG signal variability, user calibration, comfort of wearables, and user acceptance in social environments.

Future work will focus on developing a fully functional prototype that integrates hardware and mobile application, enabling real-time signal classification with user interaction. In addition, structured usability studies will be conducted to evaluate system performance, while the architecture will be extended with emotion-aware response modules. The proposed framework will further be assessed using objective benchmarks such as navigation success rate, classification accuracy, latency, and user satisfaction.

By providing a holistic, interdisciplinary foundation that merges cognitive neuroscience, wearable systems, and spatial AI, NeuroLens lays the groundwork for next-generation assistive navigation tools that are both intelligent and inclusive.

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