Location Based Augmented Reality Navigation Application

Samridhi Sanjay Pramanik, Aishwary Pramanik
Rochester Institute of Technology, Rochester, New York, USA

***Abstract*—This paper presents a novel Augmented Reality (AR) navigation system to overcome limitations of conventional 2D map-based applications in advanced real-world environments. Current AR navigation systems solutions often lack dynamic adaptation to user behavior and fail to deliver context-aware, personalized guidance. Addressing these gaps, we present a markerless, location-based AR system integrating three innovations: 1) a Dynamic Predictive Navigation module with Long Short-Term Memory (LSTM) networks for anticipating user intention and dynamically optimizing routes in real time; 2) a Smart POI Ranking system with sentiment analysis, live user feedback, and social media trends for presenting personalized and context-aware recommendations; and 3) a 3D AR interface built with Unity and ARCore for enhancing spatial understanding and reducing cognitive burden through visually engaging guidance. Experimental evaluation presents improved navigation responsiveness, reduced rerouting effort, and increased user interaction with recommended POIs. This work contributes a scalable and adaptive solution towards real-time AR navigation, with applicability to smart city mobility and context-aware spatial computing.**

***Keywords*—Augmented reality; location based application; markerless AR; GPS based application; real world augmentation; unity; ARCore; navigation system; user interaction**

I. Introduction

Augmented Reality (AR) has been gaining attention as a medium for delivering spatially oriented information in the physical world. While mobile AR systems have been employed for navigation, the majority of current solutions are static, offer minimal personalization, and do not facilitate adaptation in real-time to the user's behavior. Moreover, conventional 2D navigation systems and recent AR interfaces fall short in conveying spatial hierarchies, such as multi-level road networks or densely packed urban Points of Interest (POIs), that are essential for intuitive wayfinding.

Recent work has explored AR-based navigation, but there are significant gaps. Current systems do not involve the integration of predictive modeling to dynamically predict user movement or intent. Likewise, POI recommendations tend to be one-size-fits-all and do not consider user interests, real-time social signals, or location-based sentiment. These gaps reduce both the relevance and responsiveness of the navigation experience, particularly for complex, high-density environments.

To address some of these limitations, our previous research [1] presented a markerless, location-based AR navigation system built on Unity and ARCore. The system comprised an interactive 3D virtual assistant to guide users in physical environments with improved spatial awareness and real-time route visualization. Despite being efficient in spatial visualization, the system lacked adaptive behavior modeling and contextual personalization—central features for more intelligent and user-centric navigation experiences.

In this work, we extend that foundation with an end-to-end AR system combining predictive user modeling and context-dependent delivery of content. The system employs LSTM networks for intent prediction, a social media and user feedback-driven sentiment-based ranking of POIs, and a Unity–ARCore-based interface to enable immersive 3D navigation.

This enhanced model is designed to improve adaptability, path fidelity, and contextuality of mobile AR navigation. Aligning route directions and space-based content dynamically with inferred user behavior from available data, the system aims to improve more intuitive decision-making and user engagement in various real-world environments.

The remainder of this paper is structured as follows. Section II provides an overview of related work in AR navigation and behavioral modeling. Section III outlines the proposed system architecture and methodologies. Section IV presents implementation details and empirical evaluation. Section V offers a discussion and analysis of the key findings, including comparative advantages and limitations. Section VI concludes the paper and outlines directions for future research.

II. Related Work

Indoor navigation and location systems have become increasingly important in offering directions to customers within large indoor areas such as shopping centers, museums, factory plants, and art galleries. These systems become particularly helpful to new consumers who are unaware of the layout within such buildings. Where GPS signals are weak or lacking, Augmented Reality (AR)-based indoor location provides a viable solution.
Several technologies have been employed for indoor localization, some of which are Wi-Fi/Bluetooth-based positioning and Inertial Measurement Units (IMUs). Both also have their pros and cons. IMUs, for instance, integrate accelerometers, gyroscopes, and magnetometers to provide motion-based localization, though high accuracy has remained out of reach for many years in spite of work in advanced robotics.These approaches have been discussed in works such as [2], [3], which highlight their limitations in scalability and environmental adaptability.

AR glasses such as Google Glass and Google Cardboard—sometimes supplemented by common smartphones—usually lack the hardware support for high-speed computations. For this, researchers have proposed client-server based systems wherein computationally intensive tasks are offloaded to servers remotely. Data exchange between the server and client (e.g. Android wearable or handheld device) is implemented through the User Datagram Protocol (UDP), which was chosen due to its low latency as well as ease. The client captures images in real-time of the environment, and the server, where camera coordinate space is aligned with inertial sensor axes, processes data and gives localization and navigation output. Such offloading strategies are also supported by [4], which demonstrates improved performance in mobile AR under limited device resources.

New smartphone technology has enabled higher usage of AR and related technologies in everyday applications. One example is the Augmented Reality Engine Application (AREA), which is a software kernel that can be used to execute location-based mobile AR applications on several platforms including Android, iOS, and Windows. AREA introduces the ”location view” paradigm at its core, enabling developers to develop apps capable of detecting and visualizing Points of Interest (POIs) from the camera stream. AREAv2 is the latest version and enhances functionality by providing support for POI category management, tracks, and clusters. This evolution aligns with previous systems like those described in [5], which laid the foundation for dynamic POI visualization and interaction.

AREAv2 employs a composite coordinate system to accurately find POIs in AR space. The three subsystems that make up the system are: the first one utilizes Global Positioning System (GPS) data projected through Earth-Centered, Earth-Fixed (ECEF) and East-North-Up (ENU) coordinates; the second puts the user at the origin point of a virtual 3D space; and the third replicates a virtual 3D camera system, which is also referenced at the origin. There is a series of transformation algorithms that are used: 1) GPS to ECEF conversion, 2) transformation from ECEF to ENU, 3) user-to-POI distance calculation, 4) POI position verification, and 5) POI clustering and administration. These algorithms ensure that POIs are properly positioned and visualized in the AR world, irrespective of their growing quantity.Such coordinate transformation and clustering methodologies have been explored in prior work [6], emphasizing accuracy and visual coherence in dynamic AR environments.

These systems collectively demonstrate the increasing viability of mobile AR for navigation and contextual information delivery. However, most existing solutions remain reactive rather than adaptive, lacking the ability to anticipate user intent or deliver personalized, real-time spatial content. Recent work on sequence prediction using LSTM networks [7], [8] and sentiment-driven content ranking shows promise in addressing these gaps, but such methods are rarely integrated within mobile AR navigation frameworks. Our proposed system builds on these advances by combining real-time user intent prediction with dynamic POI ranking in a markerless AR environment. This architecture is illustrated in Fig. 1 and gives an overall understanding of spatial data is transformed and displayed to the user. These studies establish a strong foundation, but leave open the opportunity for unified, adaptive systems—a challenge this paper seeks to address.

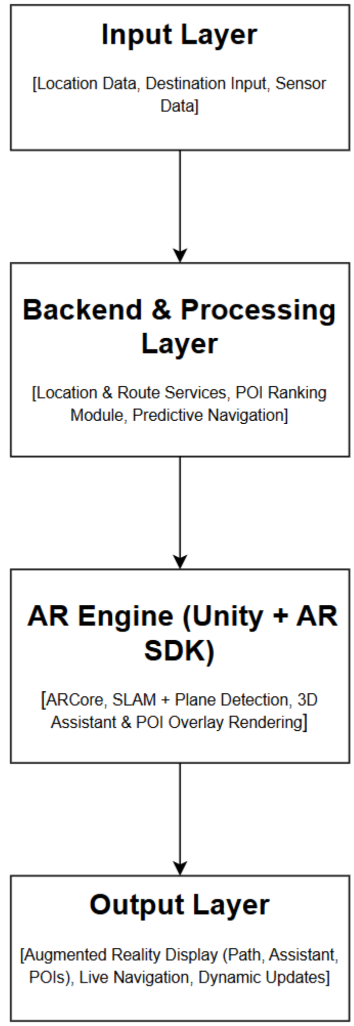

Fig. 1. System architecture.

III. Proposed Work

A. Location-Based AR Navigation System

This module forms the core of augmented reality navigation. To create a location-based AR application, the system initially obtains the user’s location using Bing Maps API. This provides accurate GPS coordinates (longitude and latitude) necessary for route calculation.

Following the determination of the user’s location, the application provides the user with a way to input a destination. Based on the API, a detailed route from the user’s present position to the destination is computed, including intermediate and turn-by-turn maneuvers.

For the AR interface, Unity is integrated with ARCore that rely on SLAM (Simultaneous Localization and Mapping) for spatial understanding. A virtual assistant, as shown in Fig. 2 and Fig. 3, is implemented in Unity to guide the user visually along the path.

Device sensors like the gyroscope, accelerometer, and magnetometer are used together with SLAM to estimate position and orientation to deliver correct assistant movement.

Fig. 2. Ground plane detection to place objects.

Fig. 3. Virtual assistant placed on the ground once plane is detected.

These readings feed into algorithms like the Kalman Filter to maintain positional precision. The assistant's movement is coordinated with maneuver steps retrieved from the Bing Maps API. Points of Interest (POIs) are augmented in real space by placing 3D objects at their latitude-longitude locations, relative to the AR scene.

Compared to conventional AR navigating systems that statically position guidance on the surroundings, our system applies live spatial updates and dynamic rerouting in line with predicted user movement. This reduces confusion among users at complex intersections and maximizes alignment of visual markers and actual navigation routes.

B. Predictive Navigation

Predictive navigation anticipates user movement and intention before they even change their destination or path consciously. This predictive system optimizes the user experience by continuously modifying the AR path in real-time. Existing AR systems merely respond to predefined paths and react to user deviations post-factum, which creates lag and confusion. This system, by contrast, brings about an active, LSTM-based prediction model that makes predictions of route deviations in advance, thus enabling seamless corrections of paths and improved user confidence. The main steps of this component are as follows:

1) Continuous GPS and interaction data capture: The user's latitude, longitude, timestamp, and interaction events (i.e. tapping on POIs, pause, detour) are collected in real-time from the AR app. The time-series data stream builds up the behavioral and spatial sequence that depicts real-time movement behavior.

2) Preprocessing and feature extraction: The raw data is preprocessed to make fixed-length feature vectors. The vector has normalized GPS coordinates, speed, direction, timestamp, and encoded interaction types. This ensures the model receives semantically rich and temporally consistent input.

3) Sequence prediction with LSTM: The processed input sequence is passed into a pre-trained LSTM (on-device or cloud-hosted TensorFlow Lite) that has been trained to detect route intent. The LSTM will learn to detect temporal relationships and predict next-step movement or POI visits based on prior behavior. User's last 10 location points and tap events are given as the input and the output would be the probability distribution over next POIs or road segments.

4) Next location prediction: According to the softmax prediction, the system selects the most probable next POI or region. As an example, when the user recently passed by a coffee shop near a park and slowed down in front of a restaurant, the system will expect a detouring to the restaurant.

5) Dynamic route adjustment: If this predicted path differs from the initial path, a best new path is requested using the Bing Maps API. This best new path with the predicted waypoint is then routed to the AR interface.

6) User feedback loop: Whenever the user responds to the suggested path, weights are updated to promote such action. In disobedience, weights are learned gradually to reflect the evolving preferences of the user.

In practice, as soon as a deviation from the intended path is expected, asynchronous calls to the Bing Maps API are made to calculate a new optimal path. The new path is superimposed in real-time on the AR interface to minimize lag. Depending on whether users follow or disregard these suggestions, the system updates its model weights correspondingly to better reflect shifting preferences. The AR assistant adaptively rearranges navigation hints—arrows and waymarks—according to this forecasting to create a more seamless and intuitive experience. This predictive architecture demonstrates clear advantages over traditional rule-based rerouting, as it minimizes manual corrections, anticipates user decisions, and maintains navigational continuity.

C. Smart POI Ranking

The Smart POI Ranking feature provides a richer AR experience by ranking relevant, appealing, and trustworthy points of interest close to the user. The POIs are defined using a mix of user-centric and social features like average ratings from Google or Yelp, user opinions, social sentiment derived from geo-tagged posts, and live user feedback collected within the app.

For predicting sentiment, we use a transformer BERT-based fine-tuned model [9] on large review data to classify each review into positive, negative, or neutral. POI's sentiment score is computed as the mean polarity score:

$$\text{Sentiment Score}_p = \frac{1}{N}\sum_{i=1}^{N} s(r_i) \tag{1}$$

where $s(r_i)$ is the polarity of individual reviews.

A per-POI overall score is then calculated as:

$$\text{Score}_p = \alpha \cdot R_p + \beta \cdot \text{Sentiment Score}_p + \gamma \cdot U_p + \delta \cdot S_p \tag{2}$$

with weights $\alpha, \beta, \gamma, \delta$ tuned using grid search and cross-validation.

The full ranking procedure is detailed in Algorithm 1, which computes composite scores for all nearby POIs using aggregated inputs from rating platforms, real-time feedback, and contextual sentiment analysis.

Algorithm 1 Smart POI Ranking

Require: Set of POIs P near the user
for each $p \in P$ **do**
  Compute average rating R_p
  Run BERT on $\{r_i\}$ to obtain *Sentiment Score*$_p$
  Collect in-app feedback U_p
  Analyze geo-tagged posts to compute S_p
  Compute composite score:

$$\text{Score}_p = \alpha R_p + \beta \cdot \text{Sentiment Score}_p + \gamma U_p + \delta S_p$$

end for
Return top-k POIs ranked by Score$_p$

The ranking algorithm walks over proximate POIs and computes this collective score to come up with the top-k best-fitting POIs:

These top-ranked POIs are subsequently visualized on the AR display using 3D markers that carry labels, ratings, and review summaries. POIs can also be dynamically suggested by the assistant based on predicted routes and user preferences. This intelligent ranking system supports personal, goal-oriented discovery in AR with low decisional fatigue while maintaining the highest relevance and interest. Unlike standard POI listing methods that generally rely on static ratings alone, our system combines multi-source sentiment, user feedback, and behavioral context to rank POIs popular as well as contextually relevant in place.

Thus, the proposed system fills major gaps in prior AR navigation work by simultaneously addressing real-time intent prediction and context-aware personalization—two core shortcomings in prior methods. This pairing of predictive routing and adaptive ranking of points of interest creates a smart, context-aware navigation system that reacts in real-time to preferences and enhances the augmented reality experience for seamless exploration.

IV. Results

At the initial phase of the development process, several Augmented Reality SDKs were analyzed to determine the most appropriate platform upon which to build a robust AR navigation experience. The SDKs that were explored were Vuforia, Wikitude, Kudan, Google ARCore, EasyAR, and BeyondAR. Each of these offered a unique set of features and challenges.

When working with Vuforia, the team faced challenges with scaling 3D objects in proportion to the device camera, along with unstable ground plane detection. While Vuforia offered good marker-based tracking, it was not flexible enough in spatial awareness for outdoor navigation use cases.

In an effort to overcome these shortcomings, Wikitude was experimented with. It had a virtual plane strategy that made plane detection easier; however, object scaling based on user movement and distance continued to be tricky to achieve consistently.

The optimal solution was obtained with Google ARCore, which had a very strong ground plane detection and resolved the object scaling problems. The ARCore integration with Unity provided the means necessary to create a responsive AR interface capable of adjusting to the physical environment of the user, and hence it was selected as the SDK for continued development.

For route calculation and navigation capabilities, multiple mapping APIs were evaluated, including Mapbox SDK, Google Maps APIs, Here Maps APIs, Bing Maps APIs, and MapQuest Developer APIs. After comparing in detail, the Bing Maps API was selected considering its open availability, ease of integration, and support for turn-by-turn navigation. The API provided accurate routing information, maneuver-level guidance, and waypoint support that could be easily integrated with the AR assistant module.

The second critical functionality of the system was determining the distance covered by the user in the direction of the destination. Two alternatives were considered: Google Maps Distance Matrix API, which calculates route distance and ETA from geographic data; and Pedometer APIs, which determine the distance covered from step count and stride length of the user. Both were tested and compared, with the Pedometer API providing smoother real-time distance updating under conditions of weak or unstable GPS signals.

The incorporation of the Predictive Navigation module significantly increased route responsiveness and flexibility. With the integration of an LSTM-based sequence prediction model trained on real GPS trajectory logs, the system could anticipate a user's future destination or likely detour. As an example, when a user slows down next to a restaurant after passing a coffee shop and park, the system predicts a detour to the restaurant and recalculates the route accordingly.

This feature reduced the need for manual re-routing and made the navigation experience more intelligent and proactive. Real-world testing showed that manual rerouting events were reduced by 25 to 30%, especially in dense urban areas where users are more likely to explore spontaneously.

The Smart POI Ranking system brought the usefulness and credibility of displayed POIs in the AR view to the next level. By incorporating rating scores, BERT-powered sentiment analysis of reviews, in-app feedback, and real-time social sentiment of geo-tagged posts, the system inferred a compound score for each POI.

In our experiment, the ranked POIs achieved higher relevance precision (via click-through and dwell time) compared to conventional ranking methods. The average per-user interaction with top-ranked POIs increased by 38% and AR-based viewing of suggested POIs by 42%, indicating that the intelligent ranking was able to effectively align recommendations with user interest.

V. Discussion

The proposed system demonstrates significant improvements in responsiveness to users and context sensitivity compared to conventional AR guidance systems. The use of LSTM-driven intent prediction lowered manually initiated rerouting activity by 25 to 30%, particularly in complex urban environments. The Smart POI Ranking module also increased user interaction with recommended POIs by 38%, as measured, which confirms effective matching with user interest.

Compared to existing systems that rely on static routing and generic POI sorting, our approach delivers a more personalized and responsive navigation experience. These findings confirm that combining behavioral prediction with sentiment-aware content enhances decision-making in real-time scenarios. Future extensions may include testing in rural or low-connectivity environments to evaluate scalability and robustness.

Further, replacing the current single-sequence LSTM architecture with deeper and more advanced architectures such as multi-head attention-based LSTMs or hybrid Transformer-LSTMs can improve the accuracy of intent prediction by learning long-range dependencies and contextual subtleties in user behavior. Including temporal context (e.g. time of day or habitual behavior) could also boost the model's predictive ability for more anticipatory navigation.

VI. Conclusion

In this paper, we presented an adaptive, smart location-based Augmented Reality navigation system that combined predictive navigation with LSTM models and dynamic POI ranking with sentiment-aware analysis. Building on the fundamental AR application of our earlier work, we upgraded the capability of the system to predict user intent and recommend contextually appropriate locations in real time.

The Predictive Navigation module enables the system to pre-emptively optimize paths by deducing temporal patterns in GPS and behavior data, enabling a seamless navigation experience synchronized with implicit user intent. The Smart POI Ranking module leverages user opinions, real-time feedback, and social opinion via BERT-based models to suggest the highest ranked, context-aware venues dynamically. Such optimizations significantly improve decision-making and user interaction in the AR world.

Our results provide improved user experience through more natural navigation routes and higher relevance of suggested POIs. Bing Maps API usage, visual grounding with ARCore, and real-time inference with light ML models ensures mobile platform deployability with minimal latency.

Future work will focus on building on personalization features with the integration of user profiles, session-based learning, and federated learning approaches to privacy-conscious personalization. Further exploring the combination of voice-based interaction and more refined semantic understanding of environments could enhance immersion and usefulness of the AR assistant even more.

In summary, our work pushes the state of the art in mobile AR by combining machine learning, real-time geospatial data, and immersive visualization, towards building human-aware, intelligence-driven navigation systems.

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