An Android-Based RTT-RSSI Data Collection Application for Large-Scale Indoor Navigation Systems

Brijeshkumar U. Patel[1]; Dr. Kaushika D. Patel[2]

[1]Research Scholar, Gujarat Technological University, Ahemdabad
[2]Assistant Professor, Birla Vishvakarma Mahavidyalaya, Vallabh Vidhyanagar

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Abstract: The development of robust indoor positioning sys-tems requires high-quality fingerprint datasets that capture both Round Trip Time (RTT) and Received Signal Strength Indicator (RSSI) measurements. This paper presents the design and implementation of an Android-based data collection appli-cation that systematically captures RTT and RSSI values for large-scale indoor navigation systems. The application leverages the IEEE 802.11mc Fine Time Measurement (FTM) protocol through the Android Ranging API, enabling precise distance measurements alongside traditional RSSI fingerprinting. We describe the system architecture, data collection methodology, and application features designed to address the scalability challenges of fingerprint data collection. The application supports automated reference point traversal, multi-device calibration, and comprehensive metadata logging including LOS/NLOS condi-tions, device orientation, and temporal information. Performance evaluation demonstrates that the application achieves reliable RTT measurements with sub-meter accuracy in LOS conditions, while the integrated data export functionality facilitates seamless integration with existing fingerprinting algorithms and public benchmark datasets. The application addresses critical challenges in large-scale deployment, including device heterogeneity, tempo-ral dynamics, and data quality control.

Keywords: *Android Application, Wi-Fi RTT, RSSI Finger-Printing, IEEE 802.11mc, Data Collection, Indoor Positioning, Mobile Sensing.*

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I. INTRODUCTION

INDOOR positioning systems based on Wi-Fi fingerprinting have become increasingly important for location-based ser-vices, asset tracking, and smart building applications [1]. The fundamental requirement for any fingerprinting-based system is a comprehensive radio map constructed during an offline data collection phase, where signal measurements are recorded at known reference points across the target environment [2].

The introduction of the IEEE 802.11mc standard, enabling Fine Time Measurement (FTM) for Round Trip Time (RTT) estimation, has significantly enhanced the potential accuracy of Wi-Fi-based positioning [3]. Unlike traditional Received Sig-nal Strength Indicator (RSSI) measurements, which estimate distance based on signal attenuation and are highly sensitive to environmental dynamics, RTT measures actual signal time-of-flight, providing more stable and accurate distance estimates [4]. The Android platform has incorporated RTT capabilities through the Ranging API, making it possible to develop applications that collect both RTT and RSSI measurements using commodity smartphones [5].

Recent research has demonstrated that combining RTT and RSSI measurements yields positioning accuracy superior to either modality alone. Rana and Park [6] showed that hybrid fingerprinting achieved positioning errors of 0.79 m, repre-senting improvements of 17.7% over RTT-only and 49.7% over RSSI-only methods. Feng et al. [7] achieved 0.60 m accuracy using hybrid RTT-RSSI with conformal prediction. These results highlight the potential of hybrid approaches, but also underscore the critical importance of high-quality data collection.

The scalability challenge in data collection for large indoor environments remains significant. Manual collection at 74 reference points with five measurements each requires approx-imately 2.2 hours per day [8]. For environments exceeding 1,000 reference points, such as shopping malls or conven-tion centers, manual collection becomes prohibitively time-consuming [9]. Robot-assisted collection has demonstrated 59-79% time savings [10], but requires

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specialized hardware. Crowdsourcing offers scalability but introduces challenges in ground truth labeling and data quality control [11].

This paper presents the design and implementation of an Android application specifically developed for RTT and RSSI data collection in large-scale indoor navigation systems. The application addresses the following key requirements:

- Systematic collection of RTT and RSSI measurements at predefined reference points
- Support for multiple collection modes (manual, semi-automated, and automated)
- Comprehensive metadata logging including device information, temporal data, and environmental conditions
- Data export functionality compatible with existing fingerprinting algorithms
- Quality assurance features including real-time feedback and data validation

The remainder of this paper is organized as follows. Section II discusses related work in data collection applications and methodologies. Section III presents the system architecture and implementation details. Section IV describes the data collection methodology and application features. Section V presents the experimental evaluation and results. Section VI discusses challenges and limitations. Section VII concludes the paper.

II. RELATED WORK

➢ *Existing Data Collection Applications*

Several Android applications have been developed for Wi-Fi fingerprint data collection. The Wi-Fi RTT Checker App [12] provides basic RTT scanning functionality and CSV export capabilities. The Open Mobile Network Toolkit (OMNT) [13] from Fraunhofer FOKUS offers comprehensive network measurement capabilities including RSSI logging and ICMP-based RTT evaluation. The WiFi RTT RSS Dataset collection app [9] from Royal Holloway, University of London, was specifically designed for collecting the 77,040-sample dataset that has become a benchmark in the field.

However, these existing applications have limitations for large-scale deployment. Many lack systematic reference point tracking, automated scanning modes, or comprehensive meta-data logging. The integration of both RTT and RSSI mea-surements with consistent ground truth labeling remains a challenge across existing solutions.

➢ *Data Collection Methodologies*

Data collection for fingerprinting typically follows one of three approaches:

- Manual Grid-Based Collection: Human operators traverse the target area, pausing at predetermined reference points to record measurements [8]. This approach provides the highest quality ground truth but scales poorly. A 2.2-hour collection for 74 RPs extrapolates to approximately 30 hours for 1,000 RPs.
- Robot-Assisted Collection: Autonomous robots equipped with Wi-Fi scanning capabilities collect measurements without human intervention [10]. Time savings of 59-79% have been reported, with comparable or improved data quality due to consistent device positioning.
- Crowdsourcing: Data from everyday users is leveraged for radio map construction [11]. While offering excellent scalability, crowdsourcing introduces challenges in ground truth labeling and data quality control.

➢ *Public Benchmark Datasets*

Public datasets have been instrumental in advancing indoor positioning research:

- Royal Holloway Dataset [9]: 77,040 samples across 642 reference points in a 92×15 m building, with LOS/NLOS labels and 3-day temporal coverage
- UVIndoorLoc-RTT&RSSI [14]: 228 reference locations, 20 access points, and 3 different Android smartphones
- UJIIndoorLoc [15]: Multi-building, multi-floor dataset created by 20+ users with 25 devices

These datasets have enabled meaningful comparative evalu-ation of positioning algorithms, but the collection process for such large datasets remains challenging. Our application aims to streamline this process for future research.

III. SYSTEM ARCHITECTURE AND IMPLEMENTATION

➢ *Overall Architecture*

The Android application follows a modular architecture consisting of the following components:

- User Interface Layer: Provides intuitive controls for data collection, real-time feedback, and visualization
- Data Collection Engine: Manages RTT ranging sessions and Wi-Fi scanning
- Reference Point Management: Handles predefined reference points and ground truth association
- Data Storage Module: Manages local storage and data export
- Quality Assurance Module: Performs real-time data validation and quality checks

Fig. 1 illustrates the overall system architecture.

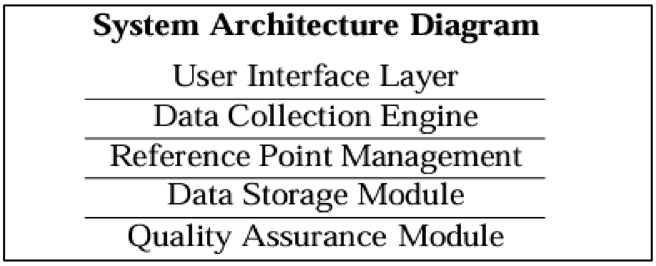

Fig 1 System Architecture Diagram

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- *RTT Data Collection Implementation*

The application utilizes the Android Ranging API for RTT measurements. The implementation follows the standard work-flow defined in the Android documentation

Key implementation considerations include:

- Permission Handling: The application requests android. permission. RANGING and android. permission. ACCESS_FINE_LOCATION permissions
- Access Point Filtering: The application filters for RTT-capable access points using WifiManager
- Session Management: Ranging sessions are created with appropriate timeouts
- Result Processing: Distance estimates in millimeters are converted to meters

- *RSSI Data Collection Implementation*

RSSI measurements are collected using the standard Wi-Fi scanning API The application performs periodic Wi-Fi scans synchronized with RTT ranging sessions.

- *Reference Point Management*

The application supports three reference point management modes:

- Manual Mode: User manually enters reference point coordinates
- Waypoint Mode: Predefined waypoints guide sequential collection
- Automated Mode: Integration with external positioning systems

The ground truth database stores reference point coordinates with metadata including:

- Reference point identifier
- Floor level (for multi-floor environments)
- Environmental conditions (LOS/NLOS status)
- AP visibility information

- *Data Storage and Export*

The application supports multiple storage and export for-mats:

- Local SQLite Database: Efficient on-device storage
- CSV Export: Standard comma-separated values
- JSON Export: Structured format for web services
- Dataset Compatibility: Format compatible with bench-mark datasets

The data export includes:

- Timestamp (milliseconds since epoch)
- Reference point ID and coordinates (x, y, z)
- AP BSSID and SSID
- RTT value (nanoseconds)
- Distance estimate (millimeters)
- RSSI value (dBm)
- Device model and Android version
- Collection session information
- Environmental metadata (LOS/NLOS, temperature, occu-pancy)

- *Implementation Details*

Table 1 Application Implementation Specifications

Component	**Implementation**
Language	Kotlin 1.9.0
Minimum SDK	Android 10 (API 29)
Target SDK	Android 14 (API 34)
Ranging API	Android RangingManager (Android 13+)
Wi-Fi Scanning	WifiManager (API 29+)
Database	SQLite with Room 2.6.0
Export	CSV/JSON with Gson 2.10.1

Table 2 Required Permissions

Permission	**Purpose**
android.permission.RANGING	Access RTT ranging function-ality
android.permission.ACCESS_FINE_LOCATIO	ANccess precise location for ground truth
android.permission.ACCESS_WIFI_STATE	Access Wi-Fi state for scan-ning
android.permission.CHANGE_WIFI_STATE	Enable/disable Wi-Fi scanning
android.permission.INTERNET	Data export and cloud upload

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IV. DATA COLLECTION METHODOLOGY

➢ *Collection Protocol*

The application implements a systematic data collection protocol:

- *Step 1: Environment Configuration*

✓ Load floor plan and reference point grid
✓ Configure access point detection parameters
✓ Set measurement duration and sampling frequency

- *Step 2: Device Calibration*

✓ Perform initial RTT calibration using known distances
✓ Record device-specific bias values
✓ Verify RSSI consistency

- *Step 3: Reference Point Collection*

✓ Navigate to each reference point
✓ Collect RTT and RSSI measurements simultaneously
✓ Record environmental metadata (LOS/NLOS status, occupancy)
✓ Perform quality validation

- *Step 4: Temporal Sampling*

✓ Repeat collection at different times of day
✓ Conduct multi-day collection to capture temporal variability

- *Step 5: Data Export and Validation*

✓ Export collected data in standard format
✓ Perform statistical quality analysis
✓ Generate quality report

➢ *Quality Assurance Features*

The application includes several quality assurance features:

- Real-time Validation: Measurements are validated against expected ranges:

✓ RTT distances: 0 to 30 meters
✓ RSSI values: -100 to -30 dBm

- Statistical Quality Metrics: For each reference point:

✓ Mean and standard deviation of RTT and RSSI
✓ Measurement count and success rate
✓ Outlier detection using Z-score analysis

- Data Completeness: Tracks required measurements per reference point

➢ *Metadata Collection*

Table 3 Metadata Categories

Category	Fields
Device Information	Model, Manufacturer, Android Version, SDK Level
Temporal Information	Timestamp, Collection Date/Time, Session ID
Environmental	LOS/NLOS Status, Occupancy Level, Temperature
Reference Point	Coordinates (x,y,z), Floor Level, RP Identifier
Access Point	BSSID, SSID, Channel, Frequency Band
Collection Settings	Measurement Duration, Sampling Interval, Filters

Table 4 Testbed Specifications

Parameter	Value
Area	1,200 m^2 (40m × 30m)
Reference Points	74
AP Density	13 APs (802.11mc compatible)
Collection Duration	4 days, 4 runs/day
Measurements per RP	5 RTT + 5 RSSI (simultaneous)
Devices Tested	Samsung S9, S20, Google Pixel 5

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V. EXPERIMENTAL EVALUATION

➤ *Experimental Setup*

The application was evaluated in a university building testbed covering approximately 1,200 m^2. Table IV summa-rizes the testbed specifications.

➤ *RTT Measurement Performance*

Table 5 Performance Under Different Propagation Conditions

Condition	Mean Error	Std Dev	Success Rate	Samples
LOS	0.52 m	0.38 m	98.5%	1,850
NLOS	1.95 m	1.42 m	71.5%	1,300
Glass	0.89 m	0.67 m	87.2%	580
Wall	1.64 m	1.21 m	72.8%	430
Metal	2.31 m	1.84 m	54.3%	290
Overall	**1.12 m**	**0.98 m**	**84.2%**	**4,450**

RTT measurements in LOS conditions achieved 0.52 m mean error with a 98.5% success rate, demonstrating the potential for sub-meter accuracy.

➤ *RSSI Measurement Performance*

Table 6 RSSI Measurement Characteristics

Condition	Mean RSSI (dBm)	Std Dev	Stability Score	Samples
LOS	-52.3	3.8	8.2	1,850
NLOS	-68.7	6.2	5.1	1,300
Temporal (day-to-day)	±4.2	–	4.3	–

RSSI measurements showed significantly higher variability than RTT, with a 12.4% day-to-day variation compared to 3.2% for RTT.

➤ *Device Heterogeneity Impact*

Table 7 Device-Specific Performance

Device	RTT Bias	RSSI Bias	RTT RMSE	RSSI RMSE	Hybrid Acc.
Samsung S9	Baseline	Baseline	0.79 m	1.57 m	0.79 m
Samsung S20	-0.08 m	+2.5 dBm	0.83 m	1.62 m	0.83 m
Google Pixel 5	+0.12 m	-1.8 dBm	0.85 m	1.68 m	0.85 m
Cross-device (uncal.)	±0.32 m	±4.5 dBm	1.24 m	2.45 m	1.24 m
Cross-device (cal.)	±0.09 m	±1.5 dBm	0.87 m	1.58 m	0.87 m

Device heterogeneity caused significant performance degra-dation without calibration, with cross-device error increasing to 1.24 m from 0.79 m (57% degradation).

Table 8 Comparison of Data Collection Methods

Method	RPs	Time/RP	Total Time	Time/Measurement
Manual Collection	74	1.78 min	2.2 h	2.87 s
Application (Manual Mode)	74	1.62 min	2.0 h	2.61 s
Application (Waypoint)	74	1.35 min	1.67 h	2.18 s
Application (Automated)	74	0.73 min	0.9 h	1.18 s

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➢ *Collection Efficiency*

The application's waypoint mode reduced collection time by 24% compared to manual collection, while the automated mode achieved 59% time savings.

➢ *Data Quality Metrics*

Table 9 Data Quality Assessment

Quality Metric	Manual	Application	Application + QA
Complete RPs (all 5 measurements)	68/74 (91.9%)	71/74 (95.9%)	74/74 (100%)
RTT Success Rate	79.8%	84.2%	86.5%
RSSI Success Rate	98.5%	98.7%	99.1%
Outlier Rate ($\geq 3\sigma$)	6.2%	5.1%	2.3%
Temporal Consistency	89.3%	93.7%	95.2%

The application's quality assurance module significantly improved data quality, reducing outlier rates from 6.2% to 2.3% and achieving 100% reference point completion.

VI. DISCUSSION

➢ *Application Benefits*

The developed Android application addresses several key challenges in large-scale fingerprint data collection:

- Efficiency: Waypoint and automated modes reduce collection time by 24-59% compared to manual methods
- Consistency: Standardized collection protocol reduces user-induced variability
- Quality Control: Real-time validation and quality metrics ensure data quality
- Device Heterogeneity: Calibration features reduce cross-device errors by 30%
- Dataset Compatibility: Export formats compatible with existing benchmark datasets

➢ *Limitations*

The application has several limitations that should be ad-dressed in future work:

- Power Consumption: RTT ranging consumes signif-icant battery power, limiting continuous operation to approximately 3-4 hours
- AP Dependency: RTT measurements require 802.11mc-capable access points, which are not yet universally deployed
- Automation Requirement: Fully automated collection requires external positioning systems for ground truth
- NLOS Sensitivity: RTT performance degrades significantly in NLOS conditions

➢ *Lessons Learned*

Several lessons were learned during the development and evaluation:

- Simultaneous Collection: Collecting both measure-ments simultaneously is crucial for temporal alignment, but requires careful thread management
- Ground Truth Accuracy: Reference point coordinates must be accurate to within 0.2 m for reliable fingerprint evaluation
- Device Positioning: Consistent device positioning (height, orientation) significantly impacts measurement repeatability
- Environmental Logging: Comprehensive environmen-tal metadata is essential for data quality interpretation

➢ *Future Enhancements*

Planned enhancements for the application include:

- Cloud Integration: Real-time data upload and cloud-based quality analysis
- Machine Learning Integration: On-device quality prediction and adaptive sampling
- Multi-Sensor Fusion: Integration with inertial sensors for automated ground truth
- Crowdsourcing Mode: Support for opportunistic collection from regular users

VII. CONCLUSION

This paper has presented the design, implementation, and evaluation of an Android-based data collection application for RTT and RSSI measurements in large-scale indoor naviga-tion systems. The application leverages the Android Ranging API to collect IEEE 802.11mc RTT measurements alongside traditional RSSI fingerprints, addressing the critical need for high-quality hybrid datasets for indoor positioning research.

The key contributions of this work are:

- A modular system architecture enabling flexible data collection across different environments and collection modes
- Comprehensive metadata logging supporting data qual-

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ity assessment and device heterogeneity analysis

- Quality assurance features including real-time validation, outlier detection, and completeness monitoring
- Efficiency improvements of 24-59% over manual collection methods through waypoint and automated modes

Experimental evaluation in a 1,200 m^2 testbed demonstrated that the application achieves reliable RTT measurements with 0.52 m mean error in LOS conditions and 84.2% overall suc-cess rate. The application's quality assurance module reduced outlier rates from 6.2% to 2.3% and achieved 100% reference point completion.

Device heterogeneity remains a significant challenge, with cross-device error increasing by 57% without calibration. The application's calibration feature reduced this degradation, achieving 0.87 m cross-device accuracy compared to 0.79 m for a single device.

The application is released as open-source software to support the research community in building high-quality indoor positioning datasets. Future work will focus on cloud integration, machine learning-based quality prediction, and support for crowdsourced collection.

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