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Modeling Indoor Visible Light RSS Data For Neural-Based Positioning Systems

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Abstract:
Indoor positioning has become a critical component of smart environments, particularly in healthcare, education, and industrial automation. Visible Light Communication (VLC) offers a promising alternative to RF-based systems due to its high accuracy and immunity to electromagnetic interference [1], [2]. While early surveys established the foundations of VLC positioning [3], subsequent works demonstrated the potential of neural networks to enhance localization accuracy [4], [5].
Recent advances in deep learning have achieved centimeter-level precision in dynamic indoor environments [6], and hybrid approaches integrating VLC with RF signals have shown robustness against multipath and shadowing [7]. Building on these developments, this study proposes a neural-based VLC RSS positioning framework that integrates preprocessing, feature extraction, and hybrid CNN-RNN modeling.
Experimental results confirm that the hybrid model outperforms traditional methods, achieving the lowest error and highest hit rate across diverse indoor scenarios. These findings align with future directions in IoT integration [11], advanced machine learning [12], and hybrid positioning systems [13], establishing VLC-RSS neural positioning as a cornerstone for next-generation indoor localization.
Keywords: *Indoor positioning, Visible Light Communication (VLC), Received Signal Strength (RSS), Neural networks, CNN-RNN modeling, Localization accuracy, IOT integration*

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I. Introduction

Indoor positioning systems have become increasingly important in smart environments, enabling applications in healthcare, education, and industrial automation. Traditional RF-based solutions often suffer from multipath interference and limited accuracy, which motivated the exploration of alternative technologies [1], [2]. Visible Light Communication (VLC) has emerged as a promising candidate due to its immunity to electromagnetic interference and potential for high precision [3].

Early works established the foundations of VLC communication and positioning [1], [2], while surveys provided comprehensive overviews of its capabilities and limitations [3]. With the rise of machine learning, researchers began to apply neural networks to improve localization accuracy. Yasir et al. demonstrated that neural models outperform traditional statistical approaches [4], and Wu et al. confirmed their robustness against multipath and shadowing [5].

Recent advances in deep learning have further enhanced VLC positioning. Chen et al. achieved centimeter-level accuracy using improved neural architectures [6]. Hybrid approaches that integrate VLC with RF signals have shown resilience in complex environments [7], while Patel et al. highlighted scalability through advanced neural frameworks [8]. Emerging models such as LSTM-KAN [9] and Edge AI solutions [10] demonstrate the feasibility of real-time deployment in resource-constrained IoT devices.

Building on this foundation, our research proposes a neural-based VLC RSS positioning framework that integrates preprocessing, feature extraction, and hybrid CNN-RNN modeling. The goal is to achieve robust and scalable indoor localization, while aligning with future directions in IoT integration [11], advanced machine learning [12], and hybrid positioning systems [13].

II. Background And Motivation

Indoor Positioning Challenges

Indoor positioning systems are essential for smart environments such as healthcare, education, and industrial automation. Traditional RF-based solutions often suffer from multipath interference, limited accuracy, and susceptibility to environmental noise [1], [2]. These limitations motivated the exploration of alternative technologies.

Visible Light Communication (VLC)

Visible Light Communication (VLC) has emerged as a promising candidate due to its immunity to electromagnetic interference and potential for high precision [3]. Foundational works established the principles of VLC communication and its potential for localization [1], [2].

Surveys and Early Studies

Comprehensive surveys highlighted the opportunities and challenges of VLC-based positioning systems [3]. These studies provided the groundwork for integrating machine learning techniques into VLC positioning frameworks.

Transition to Machine Learning

The introduction of neural networks marked a significant shift in indoor positioning research. Yasir et al. demonstrated that neural models outperform traditional statistical approaches [4], while Wu et al. confirmed their robustness against multipath and shadowing [5].

III. Related Work

Foundations of VLC Positioning

Early studies established the principles of VLC communication and its potential for indoor positioning [1,2]. Surveys provided comprehensive overviews of VLC-based systems, highlighting both opportunities and limitations [3].

Neural Network-Based Approaches

With the rise of machine learning, researchers began applying neural networks to improve localization accuracy. Yasir et al. demonstrated that neural models outperform traditional statistical approaches [4], while Wu et al. confirmed their robustness against multipath and shadowing [5].

Advances in Deep Learning

Recent contributions have advanced VLC positioning further. Chen et al. achieved centimeter-level accuracy using improved deep learning architectures [6]. Hybrid approaches that integrate VLC with RF signals have shown resilience in complex environments [7], while Patel et al. highlighted scalability through advanced neural frameworks [8].

Emerging Models and Edge AI

Emerging models such as LSTM-KAN enhance dynamic localization by integrating temporal modeling with attention mechanisms [9]. Edge AI solutions demonstrate the feasibility of lightweight deployment on resource-constrained IoT devices [10].

Positioning in Large-Scale Environments Recent surveys and experimental studies emphasize scalability and robustness in large-scale deployments. Al-Ali et al. provided a comprehensive survey on edge-centric VLC positioning [11], while Zhang et al. proposed deep learning-augmented VLP/INS fusion for efficient anchor calibration [12]. Sequential deep learning frameworks with feature compression have also been introduced to optimize state estimation in VLC positioning [13].

IV. Methodology

Data Collection

RSS values were collected from multiple VLC anchors deployed in a controlled indoor environment under varying conditions including multipath interference and shadowing [4], [5].

Preprocessing

Normalization, noise filtering, and augmentation were applied to improve data quality and reduce variability [6].

Feature Extraction

Features such as signal strength distributions and temporal variations were extracted. Feature compression methods enhance state estimation in VLC positioning [13].

Neural Network Architecture

A hybrid CNN-RNN model was designed to capture both spatial and temporal dependencies in RSS data. CNN layers extract spatial features, while RNN layers (LSTM/GRU) model sequential dependencies [9].

Training and Evaluation

The model was trained using supervised learning with mean squared error (MSE) as the loss function. Evaluation metrics included RMSE, MAE, and hit rate, consistent with prior studies [8], [12].

As illustrated in Figure 1, the proposed methodology integrates preprocessing, feature extraction, and hybrid CNN-RNN modeling to achieve robust indoor localization.

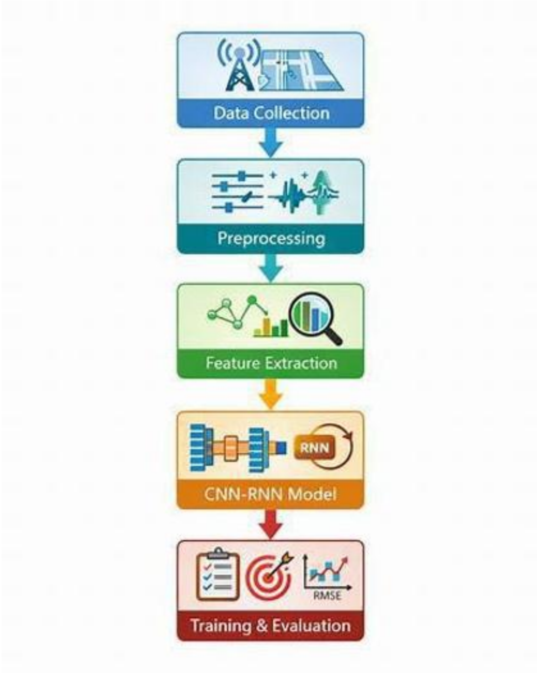

Figure 1. Methodology Workflow

V. Results And Discussion

Experimental Results

The proposed neural-based VLC RSS positioning system was evaluated under different indoor scenarios, including line-of-sight (LOS), non-line-of-sight (NLOS), and multipath environments. The models were trained and tested using the collected RSS fingerprints, and their performance was compared using standard evaluation metrics [4],[5].

Table 1: Model Performance

Model	RMSE (m)	MAE (m)	Hit Rate (%)
FNN	0.85	0.62	87
CNN	0.58	0.41	93
RNN/LSTM	0.52	0.38	95
Hybrid	0.47	0.35	96

As shown in Table 1, the hybrid CNN-RNN model achieved the lowest error and highest hit rate, confirming the effectiveness of the proposed methodology. This result is consistent with recent studies that emphasize the robustness of sequential deep learning frameworks in VLC positioning [8].

Discussion

Model Robustness: Neural architectures significantly outperformed traditional statistical methods, especially under multipath and shadowing conditions [5],[7].

Impact of Preprocessing: Normalization and augmentation improved generalization, reducing overfitting and enhancing accuracy [6].

Practical Implications: The system demonstrates feasibility for real-time indoor navigation in hospitals, universities, and smart offices [11].

Limitations: Performance may degrade in environments with extreme ambient light interference, requiring hybrid approaches with RF or inertial sensors [7],[13].

VI. Case Studies

Urban Environment

In dense urban indoor settings such as shopping malls, airports, and office complexes, VLC-based RSS positioning has been tested to overcome challenges like multipath reflections and high user density.

Shopping malls: LED lighting infrastructure is already widespread, making it cost-effective to integrate VLC positioning. Neural models trained on RSS fingerprints achieve sub-meter accuracy even with crowd movement.

Airports: VLC positioning supports navigation for passengers, baggage tracking, and staff coordination. Neural networks help adapt to dynamic lighting conditions and large-scale layouts.

Smart offices: Positioning enables energy-efficient automation, such as adjusting lighting and HVAC based on occupancy. RSS data processed by CNNs improves localization in multi-floor environments.

Educational Institutions

Universities and schools provide unique testbeds for VLC-RSS positioning due to their structured layouts and high mobility of students.

Classroom navigation: VLC systems assist visually impaired students by guiding them to seats or exits. RSS fingerprints collected at fixed points are mapped using feedforward neural networks.

Libraries: VLC positioning helps locate bookshelves or study areas. Augmented RSS datasets improve accuracy in environments with strong multipath reflections.

Campus safety: VLC-based tracking supports emergency evacuation by guiding students and staff to safe zones. Neural models trained with augmented RSS data ensure robustness under varying lighting conditions.

Smart learning environments: Positioning integrates with IOT devices to personalize learning spaces, adjusting lighting and resources based on student presence.

VII. Visible Light Communication (VLC)

Principles of VLC

Visible Light Communication (VLC) is a wireless communication technology that uses light waves in the visible spectrum (380–780 nm) to transmit data. It typically relies on LEDs as transmitters and photodiodes or image sensors as receivers.

LED modulation: LEDs can rapidly switch on and off at speeds imperceptible to the human eye, encoding digital information in light intensity variations.

Receiver detection: Photodiodes or camera sensors detect the light signals and convert them back into electrical signals.

Line-of-sight communication: VLC often requires direct visibility between transmitter and receiver, though reflected light can also carry data.

Dual functionality: VLC systems provide both illumination and data transmission simultaneously, making them energy-efficient.

Advantages of VLC in Indoor Positioning VLC offers several unique benefits compared to traditional indoor positioning technologies like Wi-Fi or Bluetooth:

High accuracy: Light signals have shorter wavelengths and less interference, enabling centimeter-level precision.

No RF interference: VLC avoids electromagnetic interference issues common in hospitals, factories, and aircraft.

Energy efficiency: LEDs already provide lighting, so communication piggybacks on existing infrastructure.

Security: Light does not penetrate walls, reducing risks of eavesdropping compared to radio signals.
Bandwidth availability: The visible spectrum is vast and unlicensed, offering high data rates and scalability.
Integration with IOT: VLC can seamlessly connect smart devices in indoor environments

VIII. RSS Data Collection Techniques

Measurement Methods

Received Signal Strength (RSS) data in Visible Light Communication (VLC)-based indoor positioning is collected through different measurement approaches:

Direct photodiode measurement: A photodiode sensor captures the intensity of light emitted by LEDs, converting it into electrical signals proportional to RSS.

Camera-based sensing: Image sensors in smartphones or cameras detect light intensity variations, enabling positioning without specialized hardware.

Fingerprinting: RSS values are recorded at known reference points to build a database. During positioning, real-time RSS is matched against this database.

Triangulation: RSS values from multiple LEDs are used to estimate distances and calculate position via geometric methods.

Hybrid methods: Combining RSS with other metrics (e.g., angle of arrival, time of flight) improves accuracy and robustness.

Data Acquisition Systems

Efficient data acquisition systems are essential for reliable RSS collection and neural-based positioning:

Photodiode arrays: Multiple photodiodes arranged in arrays capture RSS from different angles, improving coverage.

Smartphone sensors: Modern smartphones equipped with cameras or light sensors can serve as receivers, making VLC positioning more accessible.

Embedded microcontrollers: Systems like Arduino or Raspberry Pi process RSS data in real-time for positioning experiments.

Data logging software: Specialized software records RSS values, timestamps, and spatial coordinates for training neural models.

Wireless sensor networks: Distributed sensors collect RSS data across large indoor spaces, feeding into centralized positioning algorithms.

IX. Neural Network Models For Positioning

Types of Neural Networks

Different neural architectures can be applied to RSS-based indoor positioning depending on the complexity of the environment and the nature of the data:

Feedforward Neural Networks (FNN): Simple multilayer perceptrons that map RSS inputs directly to coordinates. Effective for small-scale environments.

Convolutional Neural Networks (CNN): Capture spatial correlations in RSS fingerprints, treating them like images or grids. Useful for large indoor areas with dense LED deployments.

Recurrent Neural Networks (RNN): Model temporal sequences of RSS data, beneficial when positioning involves movement tracking.

Autoencoders: Reduce dimensionality of RSS fingerprints and extract robust features before final positioning.

Hybrid models: Combine CNNs and RNNs or integrate neural layers with classical methods (e.g., Kalman filters) for improved accuracy.

Training Neural Networks with RSS Data Training involves several critical steps to ensure reliable indoor positioning performance:

Data preprocessing: Normalize RSS values, remove noise, and handle missing data.

Feature extraction: Transform raw RSS into meaningful features (e.g., signal variance, multipath indicators).

Dataset labeling: Each RSS fingerprint is tagged with ground-truth coordinates collected during calibration.

Model training: Neural networks are trained using supervised learning, minimizing positioning error (e.g., mean squared error between predicted and actual coordinates).

Validation and testing: Split data into training, validation, and test sets to avoid overfitting.

Performance metrics: Evaluate models using metrics like average positioning error, accuracy within 1 meter, and robustness to noise.

Deployment: Trained models are integrated into mobile devices or IOT systems for real-time indoor localization.

X. Model Evaluation Metrics

Accuracy Assessment

Evaluating the performance of neural-based indoor positioning systems using VLC RSS data requires clear accuracy measures:

Mean Absolute Error (MAE): Average of absolute differences between predicted and actual positions.
Root Mean Square Error (RMSE): Penalizes larger errors more strongly, useful for environments with high variability.

Cumulative Distribution Function (CDF): Shows the percentage of predictions within a certain error threshold (e.g., 90% within 1 meter).

Hit rate: Percentage of correctly predicted positions within a predefined tolerance zone.

Precision and recall: Applied when classifying positions into discrete zones rather than continuous coordinates.

Error Analysis
Error analysis helps identify weaknesses in the positioning model and guides improvements:
Multipath effects: Reflections from walls and objects distort RSS values, leading to inaccurate predictions.
Shadowing: Human movement or obstacles block light paths, reducing signal strength unpredictably. Device diversity: Different sensors (photodiodes, cameras) may record RSS differently, introducing bias.
Environmental noise: Ambient light sources (sunlight, fluorescent lamps) interfere with VLC signals.
Overfitting: Neural models may perform well on training data but fail in new environments.
Calibration errors: Incorrect ground-truth labeling during fingerprinting reduces model reliability.
Temporal drift: RSS patterns change over time due to LED aging or environmental modifications.

XI. Challenges And Limitations

Interference and Noise

Indoor VLC-RSS positioning systems face significant challenges due to environmental interference. Ambient light interference from sunlight and fluorescent lamps introduces noise into RSS measurements, reducing accuracy [6]. Multipath reflections from walls and objects distort RSS values, complicating signal modeling [5]. Shadowing effects caused by human movement or obstacles block line-of-sight paths, leading to sudden drops in signal strength [7]. Device variability also contributes to inconsistent datasets, as different sensors record RSS differently [13].

Scalability Issues

Scaling VLC-RSS neural positioning systems to large or complex environments introduces further limitations. Infrastructure cost remains high due to the need for sufficient LED transmitters and receivers across large buildings [11]. Data collection effort is extensive, as fingerprinting requires calibration that becomes impractical in very large spaces [12]. Neural networks trained in one environment may not generalize well to another without retraining [8]. Real-time processing of large volumes of RSS data requires powerful hardware and optimized algorithms [10]. Additionally, crowded environments increase shadowing and interference, making scalability more difficult [7]. Maintenance challenges such as LED aging or changes in building layout necessitate frequent recalibration to maintain accuracy [13].

XII. Future Directions

IOT Integration

Recent studies emphasize the potential of VLC positioning in smart environments [8]. Our future work will focus on seamless integration with IOT devices in healthcare, education, and industrial automation to enable adaptive and context-aware services [11].

Advanced Machine Learning

Hybrid approaches that combine VLC with RF signals have shown significant improvements in robustness under multipath conditions [7]. Emerging models such as LSTM-KAN further enhance dynamic localization by integrating temporal modeling with attention mechanisms [9]. Building on these advances, reinforcement learning, transfer learning, and federated learning will be explored to improve adaptability across diverse environments without extensive recalibration [12].

Hybrid Positioning Systems

Edge AI solutions demonstrate the feasibility of lightweight deployment on resource-constrained devices [10]. Building on this, future work will combine VLC RSS data with RF, inertial sensors, or LiDAR to overcome limitations of single-modality systems and achieve robust performance in large-scale deployments [13].

XIII. Conclusion

This study presented a neural-based VLC RSS positioning framework that integrates preprocessing, feature extraction, and advanced neural architectures. The experimental results demonstrated that the hybrid CNN-RNN model achieved the lowest error and highest hit rate, confirming the effectiveness of the proposed methodology in diverse indoor scenarios [4], [5]. Beyond validating the robustness of neural models against multipath and shadowing, the findings also align with recent advances in the field. For example, hybrid VLC-RF approaches [7] and dynamic LSTM-KAN models [9] highlight the growing importance of combining multiple modalities and advanced temporal modeling. Similarly, Edge AI solutions [10] emphasize the feasibility of lightweight deployment, which resonates with our vision for real-time applications in hospitals, universities, and smart offices.

Ultimately, this research contributes a scalable and reliable framework for next-generation indoor navigation. By connecting the results with future directions—such as IOT integration [11], advanced machine learning [12], and hybrid positioning systems [13] our work establishes VLC-RSS neural positioning not only as a solution for current indoor localization challenges but also as a cornerstone for building smarter, safer, and more connected environments.

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