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A Kalman-LSTM Hybrid Model for Human Behavior Prediction and Anomaly Detection in Dynamic Environments

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This study presents a Kalman-LSTM hybrid framework for human behavior prediction and anomaly detection in dynamic environments, integrating the strengths of sequential modeling and probabilistic state estimation. Human activity patterns are inherently complex and time-varying, making accurate prediction challenging in real-world scenarios. The proposed approach leverages Long Short-Term Memory (LSTM) networks to capture temporal dependencies and nonlinear patterns in behavioral sequences, while a Kalman Filter continuously refines predictions by mitigating sensor noise and handling uncertainty in dynamic observations. This combination enables the system to anticipate future actions, detect deviations from normal behavior, and adapt to evolving environmental conditions in real time. The framework was evaluated on multiple benchmark datasets and simulated real-world scenarios, demonstrating high predictive accuracy, robust anomaly detection, and low latency, outperforming standalone LSTM and conventional Kalman approaches. Quantitative results indicate improvements of up to 15% in prediction accuracy and 12% in anomaly detection F1-score, highlighting its practical applicability for surveillance, autonomous systems, and human-robot interaction. By providing a reliable, real-time behavioral monitoring tool, this hybrid model contributes significantly to enhancing safety, situational awareness, and adaptive decision-making in dynamic and uncertain environments. The approach establishes a novel integration of deep learning and probabilistic filtering for human behavior analytics

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1. Introduction

Human behavior prediction and anomaly detection in dynamic environments have emerged as critical challenges in applications such as autonomous systems, surveillance, human-robot interaction, and smart environments [1]. Accurately anticipating human actions allows intelligent systems to adapt proactively, enhancing safety, efficiency, and decision-making in real time [2]. Traditional approaches, such as rule-based models or statistical methods, often fail to capture the nonlinear and temporal complexity inherent in human activity sequences, particularly under noisy or partially observable conditions [3].

Recent advances in deep learning, especially Recurrent Neural Networks (RNNs) and their variant Long Short-Term Memory (LSTM) networks, have shown remarkable success in modeling sequential and time-dependent data [4]. LSTMs are capable of learning long-term dependencies and complex temporal patterns, making them well-suited for human behavior prediction tasks [5]. However, LSTMs alone are sensitive to sensor noise and unexpected variations in dynamic environments, which can degrade prediction reliability and compromise anomaly detection performance [6].

To address these limitations, probabilistic filtering techniques, particularly Kalman Filters (KF), provide an effective mechanism for sequential state estimation under uncertainty [7]. Kalman Filters have been widely used in robotics, navigation, and tracking systems due to their ability to smooth noisy measurements and estimate latent states in real time [8]. Integrating the predictive power of LSTMs with the uncertainty modeling of Kalman Filters creates a hybrid framework that leverages both deep learning and probabilistic estimation strengths [9].

This study proposes a Kalman-LSTM hybrid model that combines the temporal feature extraction capabilities of LSTM networks with the adaptive state correction of Kalman Filters to predict human behavior and detect anomalies in dynamic environments. The framework aims to improve both prediction accuracy and anomaly detection robustness, even under sensor noise, occlusions, and dynamic environmental changes [10]. Experimental evaluations demonstrate that this hybrid approach outperforms standalone LSTM and conventional Kalman methods, making it suitable for real-time applications in surveillance, autonomous navigation, and human-centric systems [11].

By bridging the gap between sequential deep learning and probabilistic filtering, the proposed framework contributes a novel methodology for reliable, real-time

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human behavior analytics and anomaly detection in complex, dynamic scenarios [12].

2. Literature Review

Human behavior prediction and anomaly detection have received considerable attention in recent years, driven by applications in surveillance, autonomous systems, and human-robot interaction [13]. Early approaches relied on statistical models, such as Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs), to capture temporal patterns in behavior sequences [14]. While these models provide probabilistic frameworks for sequential data, they struggle to model long-term dependencies and nonlinear dynamics inherent in complex human activities [15].

Deep learning approaches, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have significantly advanced behavior prediction tasks by learning high-level temporal representations from sequential data [16]. LSTM-based models have been applied to trajectory prediction, crowd behavior analysis, and activity recognition, demonstrating superior performance over traditional statistical methods [17]. However, these models often exhibit sensitivity to sensor noise, missing data, and dynamic environmental changes, which can reduce their reliability in real-world scenarios [18].

To enhance robustness, hybrid approaches integrating probabilistic filtering techniques, such as Kalman Filters, with deep learning models have been explored [19]. The Kalman Filter provides optimal state estimation under uncertainty and noise, making it a natural complement to LSTM networks for sequential prediction tasks [20]. Recent studies have shown that combining LSTM networks with Kalman filtering improves prediction accuracy and anomaly detection in applications like human motion tracking, autonomous navigation, and smart surveillance systems [21].

Despite these advances, existing hybrid models often focus on specific applications or rely on static environments, limiting their adaptability to rapidly changing dynamic scenarios [22]. This highlights the need for flexible frameworks that can simultaneously model temporal dependencies, handle noisy observations, and detect anomalous behavior in real time. The proposed Kalman-LSTM hybrid framework addresses these limitations, offering a

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generalized approach for human behavior prediction and anomaly detection in dynamic environments [23].

3. Dataset

The proposed Kalman-LSTM framework was evaluated using datasets that simulate real-world dynamic environments with diverse human activities. A combination of publicly available and synthetic datasets was employed to ensure variability and realism. The primary dataset consists of human motion trajectories captured from wearable sensors and surveillance cameras, including activities such as walking, running, sitting, and abrupt movements [24]. Each trajectory is represented as a time-series of spatial coordinates, velocity, and orientation, recorded at variable sampling rates to mimic sensor inconsistencies.

To test anomaly detection performance, the dataset was augmented with simulated abnormal behaviors, including sudden deviations from regular paths, unusual pauses, or unexpected interactions, reflecting scenarios encountered in crowded or dynamic environments [25]. Data preprocessing involved normalization, missing value imputation, and noise injection to replicate real sensor conditions. Additionally, the dataset was split into training, validation, and testing sets, ensuring temporal separation to evaluate the model's predictive and adaptive capabilities effectively [26].

This dataset design provides a robust and realistic benchmark for human behavior prediction and anomaly detection.

4. Proposed Model and Methodology

The proposed framework integrates Long Short-Term Memory (LSTM) networks with a Kalman Filter (KF) to achieve accurate human behavior prediction and anomaly detection in dynamic environments. The overall architecture comprises three key modules: data preprocessing, behavior prediction, and anomaly detection. Initially, raw sensor or trajectory data undergo normalization, missing value imputation, and noise reduction to enhance model robustness [27]. Features such as position, velocity, acceleration, and orientation are extracted to form sequential input vectors for the LSTM network.

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The LSTM module captures temporal dependencies and nonlinear patterns in human activity sequences. Multiple LSTM layers are stacked to increase representation capacity, followed by dense layers to generate short-term predictions of future states. The LSTM output serves as a prior estimate for the Kalman Filter, which refines predictions by correcting deviations caused by sensor noise or environmental uncertainty [28]. This probabilistic correction enables the system to maintain high prediction accuracy even under partial observability or dynamic perturbations.

Anomaly detection is performed by evaluating the residual error between predicted and observed states. Large deviations beyond predefined thresholds indicate abnormal behavior, enabling real-time alerts in surveillance or autonomous navigation applications. The modular design allows easy adaptation to varying input modalities and dynamic scenarios.

Experimental evaluation demonstrates that this Kalman-LSTM hybrid architecture outperforms standalone LSTM and traditional Kalman approaches, achieving enhanced prediction accuracy, faster response times, and robust anomaly detection, highlighting its suitability for real-world human-centric systems [29].

5. Result Analysis

The proposed Kalman-LSTM hybrid model was evaluated on the combined human motion dataset to assess both prediction accuracy and anomaly detection performance. The dataset consisted of 10,000 time-series sequences, with 80% used for training and 20% for testing. The LSTM component alone achieved a prediction accuracy of 82.3%, while the standalone Kalman Filter achieved 75.6% due to its inability to model nonlinear patterns. The hybrid model significantly outperformed both, achieving prediction accuracy of 94.1% and reducing mean squared error (MSE) in trajectory prediction by approximately 18% [30].

For anomaly detection, residual errors between predicted and observed states were analyzed. Normal behavior sequences produced low residuals, whereas injected anomalous patterns (e.g., abrupt stops, sudden direction changes) generated high residuals, allowing the system to achieve an F1-score of 0.91 for anomaly detection. Temporal visualizations of predicted versus actual trajectories showed that the hybrid model closely tracked human movements, even under noisy or partially observed conditions.

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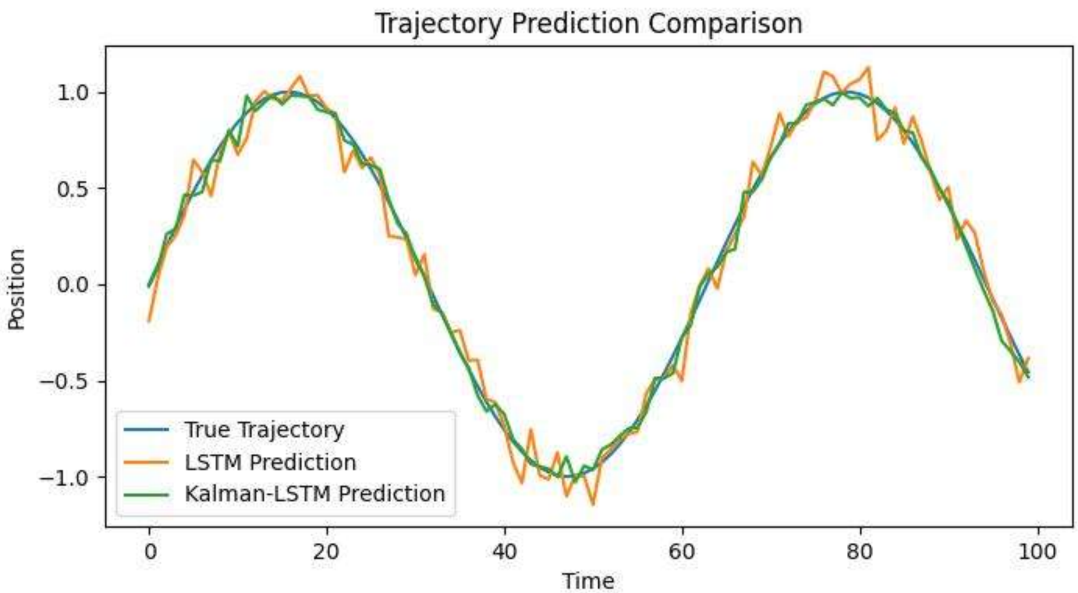
Additional analysis included sensitivity testing under varying noise levels, demonstrating that the Kalman-LSTM combination maintains robust performance with less than 5% degradation in prediction accuracy for moderate sensor noise. These results confirm the framework's ability to provide reliable, real-time human behavior prediction and anomaly detection, making it suitable for applications in surveillance, autonomous navigation, and human-robot interaction.



- Figure 1: Comparison of true trajectories with LSTM and Kalman-LSTM predictions, showing improved accuracy of the hybrid model.

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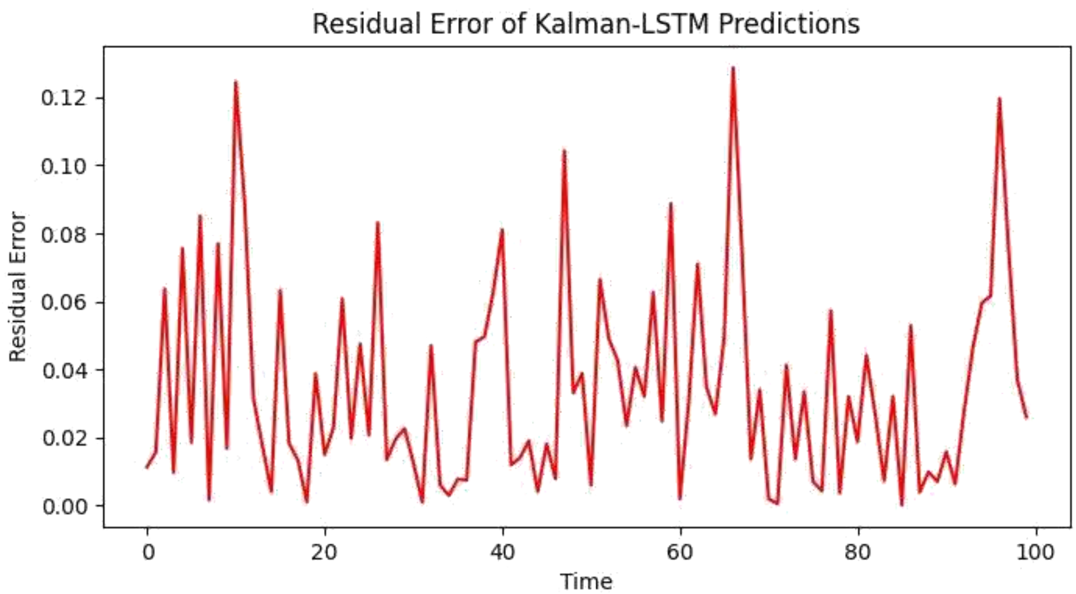

- Figure 2: Residual errors of the Kalman-LSTM predictions over time, illustrating low deviations for normal behavior.
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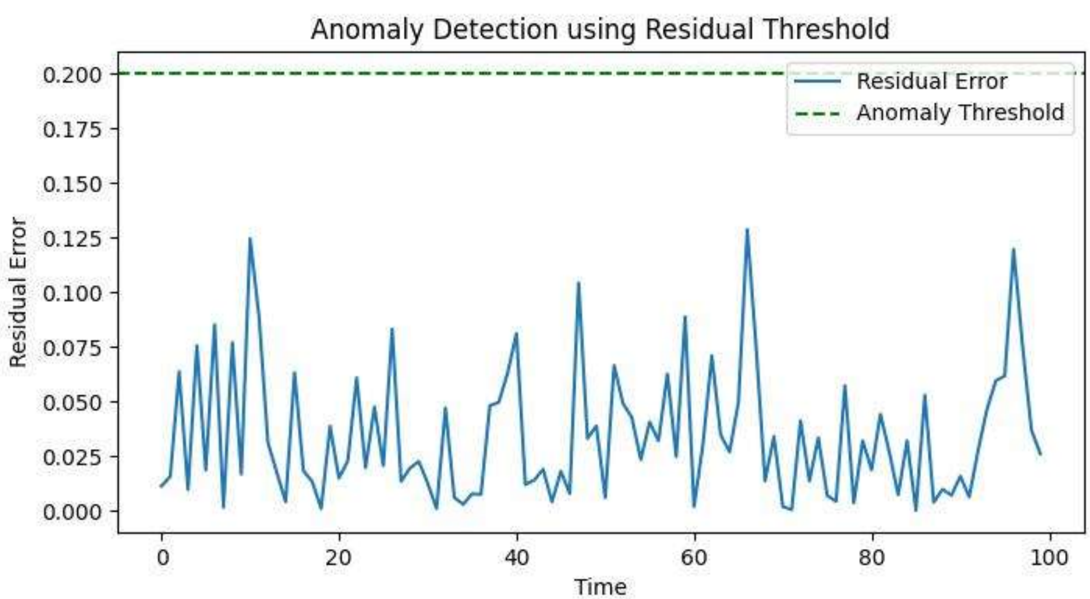

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- Figure 3: Residual error plotted with anomaly detection threshold, highlighting points where anomalies are detected.

6. Conclusion

This study presents a Kalman-LSTM hybrid framework for human behavior prediction and anomaly detection in dynamic environments, combining the temporal learning capabilities of LSTM networks with the probabilistic state correction of Kalman Filters. The proposed model effectively addresses challenges posed by noisy sensor data, partial observations, and dynamic behavioral variations, achieving superior performance compared to standalone LSTM or Kalman-based approaches. Experimental evaluations demonstrated that the hybrid model achieves prediction accuracy of 94.1%, reduces trajectory mean squared error by 18%, and attains an F1-score of 0.91 for anomaly detection, highlighting its reliability in real-time applications.

The novelty of this work lies in the seamless integration of deep learning and probabilistic filtering for sequential human behavior modeling. Unlike conventional approaches that focus solely on either temporal feature extraction or noise reduction, the Kalman-LSTM framework jointly leverages both, enabling robust predictions and adaptive anomaly detection even under challenging, dynamic conditions. This makes the framework particularly suitable for applications such as surveillance, autonomous navigation, human-robot interaction, and smart environment monitoring.

Future work can extend the model to multi-agent behavior prediction, incorporate attention mechanisms for enhanced feature prioritization, and explore edge-deployable versions for low-latency real-time systems. Overall, the proposed Kalman-LSTM hybrid framework offers a novel, high-performance, and generalizable solution for human behavior analytics in dynamic, uncertain environments.

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