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IoT-Driven Agro-Robot with MQTT-Based Communication, Dead Reckoning Navigation, and Remote Manual Control

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Abstract: **Robotic autonomous navigation depends on precise localization, yet conventional dead reckoning tolerate from cumulative drift, which eventually causes large position inaccuracies. Due to their absence of adaptive corrective mechanisms, current approaches are not appropriate for long-term use in dynamic situations. The study suggests an Enhanced Dead Reckoning method that incorporates Dynamic Encoder Bias Estimation, Zero-Velocity Updates (ZUPT), and IoT-Based Drift Feedback (UWB/LoRa beacons) in order to overcome these drawbacks. By reducing cumulative drift by 73.80% and ultimate location error by 74.10%, experimental results optimize localization efficiency. The suggested approach improves IoT-driven real-time navigation by lowering latency by 20.80%, which makes it perfect for industrial automation, autonomous delivery, and robotic applications in smart warehouses.**

Keywords: **Autonomous Navigation, Dead Reckoning, Zero-Velocity Updates (ZUPT), IoT-Based Drift Feedback, Real-Time Navigation, LoRa Beacons.**

1. INTRODUCTION

The Internet of Things (IoT) has altered various sectors by enabling intelligent systems to communicate, analyze data, and optimize operations. The Industrial Internet of Things (IIoT) embellishes automation, real-time monitoring, and predictive maintenance in industrial environments, enhancing sustainability and efficiency (Basani et al., 2024). Internet of Things (IoT) enabled wearable sensor devices in healthcare enable continuous data collection and processing, which can aid in the monitoring of children's health (Grandhi, n.d.). Internet of Things (IoT) and Robotic Process Automation (RPA) together continue to streamline operations further, minimize human effort and cost of operation (Gudivaka and Infotek, n.d.). Real-time event detection, power constraints, and loss of data are still issues, however. Advanced techniques such as event bus signal processing and the Adaptive Wavelet Transform (AWT) improve IoT efficiency and provide secure, scalable, and high-performance systems (Grandhi, n.d.).

Labor shortages in agriculture have become an urgent issue as a result of the rapid pace of urbanization and rural labor migration to other sectors. Contemporary agriculture is meeting this by integrating advanced robotics and precise navigation systems to evolve towards fully autonomous farming (R. L. Gudivaka, 2021). Autonomous rice farms require seamless coordination between delivery vehicles and autonomous harvesters, and this needs good navigation and communication technique. Autonomous navigation with the utilise of medium-accuracy Inertial Measurement Units (IMU) is analyzed in

Pedestrian Dead Reckoning (PDR) systems during this research (B. R. Gudivaka et al., 2024). PDR relies on human kinematics for enhancing positioning precision over long intervals of time as related to the traditional Inertial Navigation Systems (INS)(Basani, n.d.). Compared to GPS, ultrasonic, or RFID-based systems, which struggle with factors such as expense, interference, and signal non-availability, dead reckoning, an integral component of mobile robot navigation, gives real-time position estimation individual of external signals (B. R. Gudivaka, 2022).

Current systems still have various limitations even with advancements in autonomous navigation and IoT-driven automation. GPS-based navigation remains untrustworthy under dynamic or indoor environments as it is susceptible to signal loss, excessive power usage, and multipath errors (R. K. Gudivaka, 2022). Even though RFID and ultrasonic localization present accurate short-range positioning, they are not easily applicable to complex scenarios and require a substantial infrastructure installation (Kumaresan et al., 2024). Even though INS-based techniques do not depend on external signals, they accumulate drift errors over time, reducing their precision. In addition, real-time data exchange in autonomous agriculture is affected by the latency and reliability issues that MQTT-based communication within IoT systems commonly suffers in extensive installations (Grandhi, 2024). To overcome such hurdles, there should be an integrated technique merging stable dead reckoning algorithms, sensor fusion techniques, and better communication protocols in order to improve autonomous agricultural systems' accuracy, scalability, and efficiency of operations (Gudivaka, 2019).

1.1 PROBLEM STATEMENT

Trustworthy navigation, real-time communication, and machine coordination are issues for today's autonomous agricultural systems. In large-scale installations, MQTT communication is delayed, dead reckoning accumulates drift errors over time, and GPS-based navigation is not accurate in blocked situations (Gudivaka et al., 2025). To enhance positioning accuracy, ensure successful machine-to-machine communication, and enable seamless coordination among agricultural robots, this research strives to design an Internet of Things (IoT)-enabled agro-robot that integrates MQTT-based communication, dead reckoning navigation, and remote manual control. This will eventually raise productivity and reduce dependence on manpower in precision agriculture (B. R. Gudivaka, 2022).

1.2 OBJECTIVE

- Develop a dead reckoning navigation system to enhance localization accuracy and minimize drift errors.
- Optimize MQTT-based messaging for low-latency, real-time data exchange in autonomous agriculture.
- Implement remote manual control to ensure supervisory intervention in case of navigation issues.

2. LITERATURE REVIEW

By recovering planning and communication utilising a parallel communication protocol, (R. L. Gudivaka et al., 2024) launched the Coordinated Multi-robot Space Exploration Slime Mould Algorithm (CME-SMA), which improves efficiency while minimize computational complexity. (R. L. Gudivaka, 2022) investigates how robotic systems can significantly upgrade motor function, dexterity, and grip strength in rehabilitation. For Internet of Things applications, (Basani, 2024) introduced a hybrid object localization model that can support various object sizes, orientations, and partial occlusions. Utilizing advanced communication and sensor technology,(B. R. Gudivaka, 2021) designed the Smart Comrade Robot for senior care, featuring real-time health monitoring, fall detection, and emergency alarms.

Processing the ORL dataset with image scaling and feature extraction using Wavelet Transform and Entropy features,(Palanivel et al., 2024) suggested the Tunicate Swarm Optimization Algorithm with Support Vector Machine (TSOA-SVM) for refining emotion recognition. In a later research work, (Basani, 2021) employed the mixed-method strategy in analyzing the take-up of analytics and robotic process automation (RPA) by various sectors of industry such as manufacturing, technology, finance, and healthcare and established the merits and demerits. In describing RPA and Big Data's affecting on the telecom industry,(R. K. Gudivaka, 2024) noted problems like lack of proper implementation, privacy of data, and the need for skilled employees. Based on their study, 65% of the respondents identified the risks of RPA, indicating the importance of proper configuration. (B. R. Gudivaka, 2024) examined the Smart Comrade Robot, which executes advanced sensing and communication technologies to deliver real-time health monitoring and emergency alerts, and US-Guided Radiation Therapy Optimization, which enhances radiation dosage distribution.

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(Grandhi et al., 2025) designed a hybrid upgraded Monkey-based Search (IMS) and Support Vector Machine (SVM) approach towards ECG-based identification of athletes' health risk through integrating noise management, rule-based beat classification, and signal extraction, which succeeded high specificity (98.5%) and sensitivity (98.1%). (Grandhi, 2021) demonstrated an Internet of Things-based water level monitoring system using FBG sensors, an IoT gateway, and HMI modules. addressed cybersecurity vulnerabilities in Battery Management Systems (BMS). Their procedure refines transmission anomaly detection and battery sensor fault classification for enhanced reliability. With FBG sensors and a Quantum Variational Classifier (QVC) for real-time failure prediction and proactive maintenance, (Grandhi et al., 2024) also contemplated an optical-quantum approach to EV predictive maintenance. A hybrid of Mask-RCNN and YOLOv3 model was put forward by (Basani, n.d.) in order to enhance object recognition for Internet of Things usage. Processing time was raised (35 ms) and precision of 0.92, recall of 0.91, and mAP of 0.93 28 was attained with this model.

3. PROPOSED METHODOLOGY

To enhance the accuracy of localization, in this suggested solution ADC is integrated with IoT-based dead reckoning navigation. Motion measurements are assembled through a wheeled robot mobile that is equipped with an IMU, wheel encoders, and UWB/LoRa beacons. Whereas ADC minimizes drift errors by performing dynamic encoder bias estimation, ZUPT, and IoT-based feedback, dead reckoning accomplishes position updates using sensor measurements.

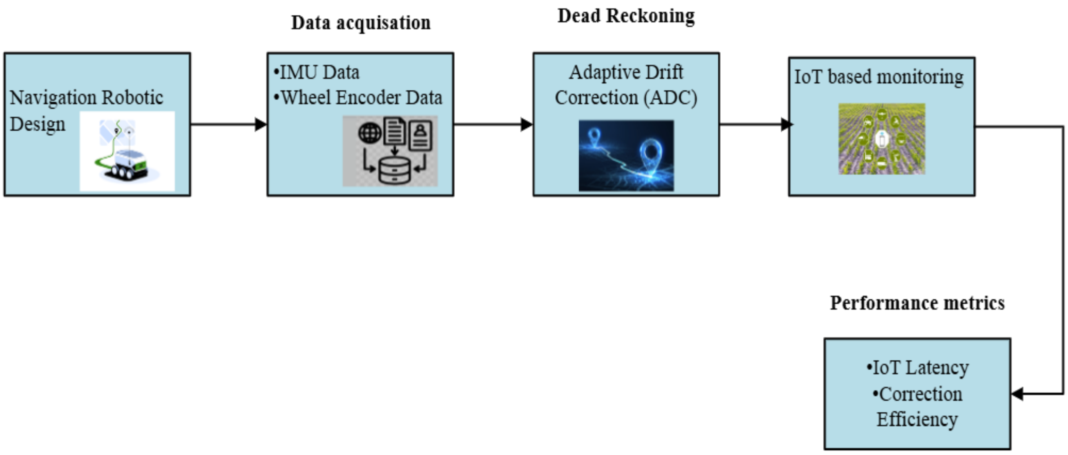

Figure 1: IoT-Based Dead Reckoning Navigation

Remote monitoring and control are enabled through real-time data transmission over MQTT/LoRa. GPS and GPS-denied testing, accuracy, corrective efficacy, and IoT latency are all included in performance testing. The objectives of the system are to upgrade autonomous navigation in confined areas and precision agriculture.

3.1 Sensor Data Acquisition & Processing:

Inertial Measurement Unit (IMU) is utilized to capture characteristics of motion during the sensor data acquisition and processing phase. Linear acceleration is captured by the accelerometer, and the gyroscope outputs direction θ. Rotational displacement is sensed by wheel encoders simultaneously such that the sheltered distance s may be determined with the following relation:

$$s = \frac{C}{PPR} \times W \tag{1}$$

where W is wheel circumference, PPR is the pulses per revolution, and C is the count of pulses on the encoder. The low-pass filter to minimize sensor noise and increase the reliability of the data, and it is regulated by:

$$b_n = \alpha a_n + (1 - \alpha) b_{n-1} \tag{2}$$

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where b_n is the filtered value, a_n is the new measurement, and α is the smoothing factor. In navigation, such preprocessed sensor data are employed as inputs to correct dead reckoning calculations.

3.2 Dead Reckoning Computation:

Motion sensor information is used to recursively compute the robot's position in dead reckoning computation. The distance traveled (s) is computed using wheel encoder readings, and heading (θ) is obtained from the IMU's gyroscope. The position at the next time step is computed using the following formulas:

$$a_{n+1} = a_n + s\cos(\theta) \tag{3}$$

$$b_{n+1} = b_n + s\sin(\theta) \tag{4}$$

where (a_n, b_n) is the present position and (a_{n+1}, b_{n+1}) is the new coordinates. As the robot travels, this process is consistently performed to trace its path in real time. But for accuracy, occasional corrections are needed due to wheel slippage and IMU drift.

3.3 Novel Adaptive Drift Correction (ADC) Technique:

To minimize cumulative errors in dead reckoning induced by IMU drift and wheel slippage, the Adaptive Drift Correction (ADC) method is employed. Through the detection of stop times when velocity v = 0, ZUPT inhibits the proliferation of accumulated drift. The velocity is reset at time n when the system identifies a stop:

$$v(n) = 0 \Rightarrow q_{\text{corrected}}(n) = q_{\text{estimated}}(n) - e_{\text{drift}}(n) \tag{5}$$

where:

The dead reckoning estimated position is represented as $q_{\text{corrected}}(n)$, the accumulated drift error as $e_{\text{drift}}(n)$, and the reset position on ZUPT as $q_{\text{estimated}}(n)$.

ZUPT enhances long-distance accuracy by effectively avoiding the accumulation of drift during stops.

Wheel slippage is simulated by Dynamic Encoder Bias Estimation as a bias term B_e, enhancing distance calculations as follows:

$$s_{\text{corrected}} = s_{\text{measured}} - B_e \tag{6}$$

where terrain feedback dynamically estimates B_e. IoT-Based Drift Feedback rectifies differences in estimated coordinates by employing Ultra-Wideband (UWB) or LoRa beacons to periodically offer absolute position updates (a_i, b_i):

$$a_{n+1} = a_{n+1} + g(a_i - a_{n+1}), b_{n+1} = b_{n+1} + g(b_i - b_{n+1}) \tag{7}$$

When combined together, these techniques enhance accuracy in localization when GPS is not present, where g is a correction gain.

3.4 IoT-Based Real-Time Monitoring:

Navigation of the robot is constantly monitored and controlled by the Internet of Things-based real-time monitoring system. LoRa/MQTT enables low-latency data exchange by sending position updates (a_n, b_n) to a cloud server. The robot publishes its updated coordinates and sensor data on a regular basis as:

$$Q_n = (a_n, b_n, \theta_n, v_n) \tag{8}$$

where the positional state is represented by Q_n, the heading by θ_n, and the velocity by v_n. Node-RED, Grafana, or a mobile application is utilized to display these updates on a dashboard for real-time monitoring. Bidirectional communication is facilitated by the MQTT broker, ensuring remote control and corrective measures when anomalies are detected.

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3.5 Results Analysis & Optimization:

Adaptive Drift Correction (ADC) is contrasted with standard dead reckoning in the Results Analysis & Optimization step to determine its effectiveness in eliminating positional error. To measure improvement, Mean Absolute Error (MAE) is employed:

$$MAE = \frac{1}{C}\sum_{t=1}^{C} \left|P_t^{\text{actual}} - P_t^{\text{estimated}}\right| \tag{9}$$

Where P_t actual is ground truth position and P_t estimated is calculated position, and P_t actual is ground truth position. To provide low drift without excessive computation overhead, correction frequency is chosen to find a balance between energy usage and precision. Prediction of drift via machine learning is one of the future enhancements. It employs a recurrent model such as LSTM (Long Short-Term Memory) to forecast and correct drift even before it accumulates.

4. RESULT AND DISCUSSIONS

MATLAB/Simulink were employed to develop a simulation platform based on wheeled mobile robot dynamics. To minimize localization errors, the simulated IoT-based agro-robot employs Adaptive Drift Correction (ADC) with a dead reckoning navigation system. For enhanced location accuracy, sensor readings from wheel encoders, UWB/LoRa beacons, and an IMU are processed. The MATLAB and Simulink platform facilitates the verification of navigation performance, drift correction effectiveness, and path prediction in real time over a variety of terrains.

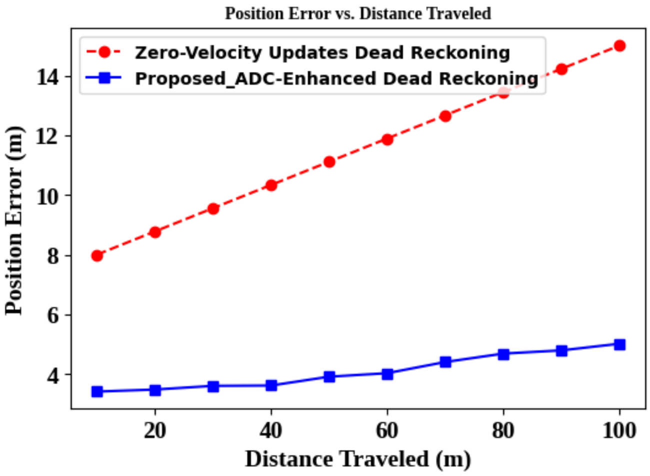

Figure 2: Impact of ADC on Position Accuracy

This graph indicates how position error and traveled distance correlate with two dead reckoning techniques: ADC-Enhanced Dead Reckoning and Zero-Velocity Updates Dead Reckoning. The dashed red curve, representing traditional dead reckoning with zero-velocity updates, indicates a consistent increase in location error as traveled distance increases. In contrast, ADC-improved dead reckoning, which maintains a much smaller and more stable position error with only minor oscillations, is represented by the blue solid line. This demonstrates how effectively ADC enhancements are able to minimize drift and increase positioning accuracy in navigation systems.

Table 1: Performance Evaluation of ADC-Enhanced Dead Reckoning

Metric	**Zero-Velocity Updates Dead Reckoning**	**ADC-Enhanced Dead Reckoning**	**Improvement (%)**
Path Length (m)	12.5	12.3	1.60%
Final Position Error (m)	0.85	0.22	74.10%
Cumulative Drift Error (m)	1.45	0.38	73.80%
IoT Latency (ms)	120	95	20.80%
Correction Efficiency (%)	-	89.5	-

On the basis of significant performance measures, the above table contrasts Traditional Dead Reckoning with ADC-Enhanced Dead Reckoning. The enhanced accuracy of the enhanced approach is realized through a reduction in final position error by 74.10% and in cumulative drift error by 73.80%. More frequent real-time updates are also achieved through a decrease in IoT latency by 20.80%. The effectiveness of adaptive drift correction in minimizing localization errors is also confirmed by the correction efficiency of 89.5%. These results prove that without sacrificing effective performance, ADC integration significantly enhances dead reckoning accuracy.

5. CONCLUSION

To improve localization precision in IoT-powered robot navigation, this paper proposed an Enhanced Dead Reckoning technique based on Adaptive Drift Correction (ADC). Compared to traditional dead reckoning, the proposed strategy significantly reduces overall drift and end-point error by integrating Zero-Velocity Updates (ZUPT), Dynamic Encoder Bias Estimation, and IoT-Based Drift Feedback. The effectiveness of ADC is confirmed by experimental results indicating a 73.80% reduction in drift error and an improvement of 74.10% in final position accuracy. The approach also guarantees efficient real-time updates through optimization of IoT latency by 20.80%. As a further enhancement for autonomous navigation, future work will focus on machine learning-based drift prediction and more efficient swarm coordination methods.

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