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Inertial Navigation System for Aircraft and Spacecraft

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Abstract

This research investigates the integration of Machine Learning (ML) algorithms into Inertial Navigation Systems (INS) to address the growing limitations faced by traditional INS in increasingly complex aerospace missions. While reliable, traditional INS suffer from accumulating errors over time due to sensor noise and integration drift [1]. This project proposes incorporating sophisticated algorithms like Genetic Algorithms and Artificial Neural Networks to dynamically correct these errors, re-calibrate sensors, and compensate for drift in real time. This innovative approach has the potential to revolutionize aerospace navigation by providing highly accurate and reliable systems, paving the way for advancements in exploration and pushing the boundaries of human ingenuity in space.

1. Introduction

Space exploration demands ultra-precise navigation for mission success and safety. Inertial Navigation Systems (INS), which estimate a vehicle's position without external references, have been crucial, even surpassing traditional methods in accuracy. However, increasingly complex missions expose limitations in traditional INS.

This report explores integrating Machine Learning (ML) into INS to improve its accuracy and address these limitations. Sensor errors and drift inherent to INS gradually reduce its accuracy. The reliance on reliable navigation necessitates more robust INS technology. Existing algorithms struggle to handle sensor errors, drift, and maintaining accurate estimates.

By integrating machine learning, this research aims to overcome these challenges and pave the way for the next generation of highly accurate navigation systems, ultimately furthering space exploration.

2. LITERATURE REVIEW

The study by Pukhov and Cohen (2020) presented a novel approach leveraging Neural Networks to enhance the performance of Inertial Navigation Systems (INS) [2]. While their work provided valuable insights, it focused primarily on the improvement of INS performance without explicit consideration for recording data along the z-axis. In contrast, this current research extends their work by incorporating a comprehensive data recording approach that encompasses not only the x and y axes but also the z-axis, offering a more holistic assessment of navigation accuracy.

Additionally, our study introduces a comparative analysis of various algorithms within the INS framework, exploring their efficacy in diverse trajectory patterns. Unlike the singular focus in Pukhov and Cohen's work, which employed a specific neural network approach, our research investigates multiple algorithms to discern the most effective integration into the INS. By incorporating these enhancements, this study aims to build upon and contribute to the advancements initiated by Pukhov and Cohen, broadening the scope and applicability of machine learning techniques in inertial navigation systems.

Furthermore, addressing the challenges observed in Vision- Aided Inertial Navigation systems, the work by Mourikis et al. (2009) in "Vision-Aided Inertial Navigation for Spacecraft Entry, Descent, and Landing" highlights the limitations of these systems in dynamically changing environments [3]. Specifically, the vision-aided system may falter when the surroundings undergo significant alterations, as seen in cases of environmental changes or extensive construction and infrastructure development. Our research aims to contribute insights that address and potentially mitigate such challenges, particularly focusing on scenarios where the environment undergoes substantial transformations, ensuring the robustness and reliability of Inertial Navigation systems.

3. METHODOLOGY

This research investigates the effectiveness of various Ma- chine Learning (ML) models in mitigating errors and enhancing the accuracy of Inertial Navigation Systems (INS). The methodology focuses on comparing the performance of three specific model.

A. Algorithms tested

- **Neuro Evolution of Augmented Topologies (NEAT):** This evolutionary algorithm automatically discovers and optimizes the architecture of neural networks, allowing for the creation of efficient and adaptable models.
- **Artificial Neural Networks (ANN) with gradient descent:** This traditional approach utilizes a pre-defined network structure and employs gradient descent optimization to adjust the network weights during training.
- **Simulated Annealing:** This optimization algorithm iteratively searches for the minimum of a complex function, potentially escaping local minima and finding a more globally optimal solution.

B. Inertial Navigation System

This research employs a custom-designed INS for data acquisition and model assessment. The system adopts a twin- dial configuration, mimicking the conventional aircraft attitude indicator and heading indicator for intuitive data interpretation and visualization during both training and evaluation phases.

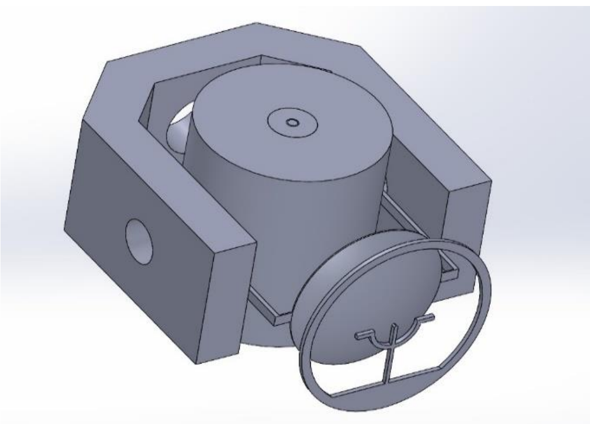

Fig. 1. Isometric view of the attitude indicator

Figure 1 shows dial that incorporates a flywheel powered by a Brushless Direct Current (BLDC) motor. These flywheels leverage their rotational inertia to provide an angular orienta- tion reference. The rotary encoders associated with each dial convert their analog rotation into a digital signal suitable for processing by the machine learning models.

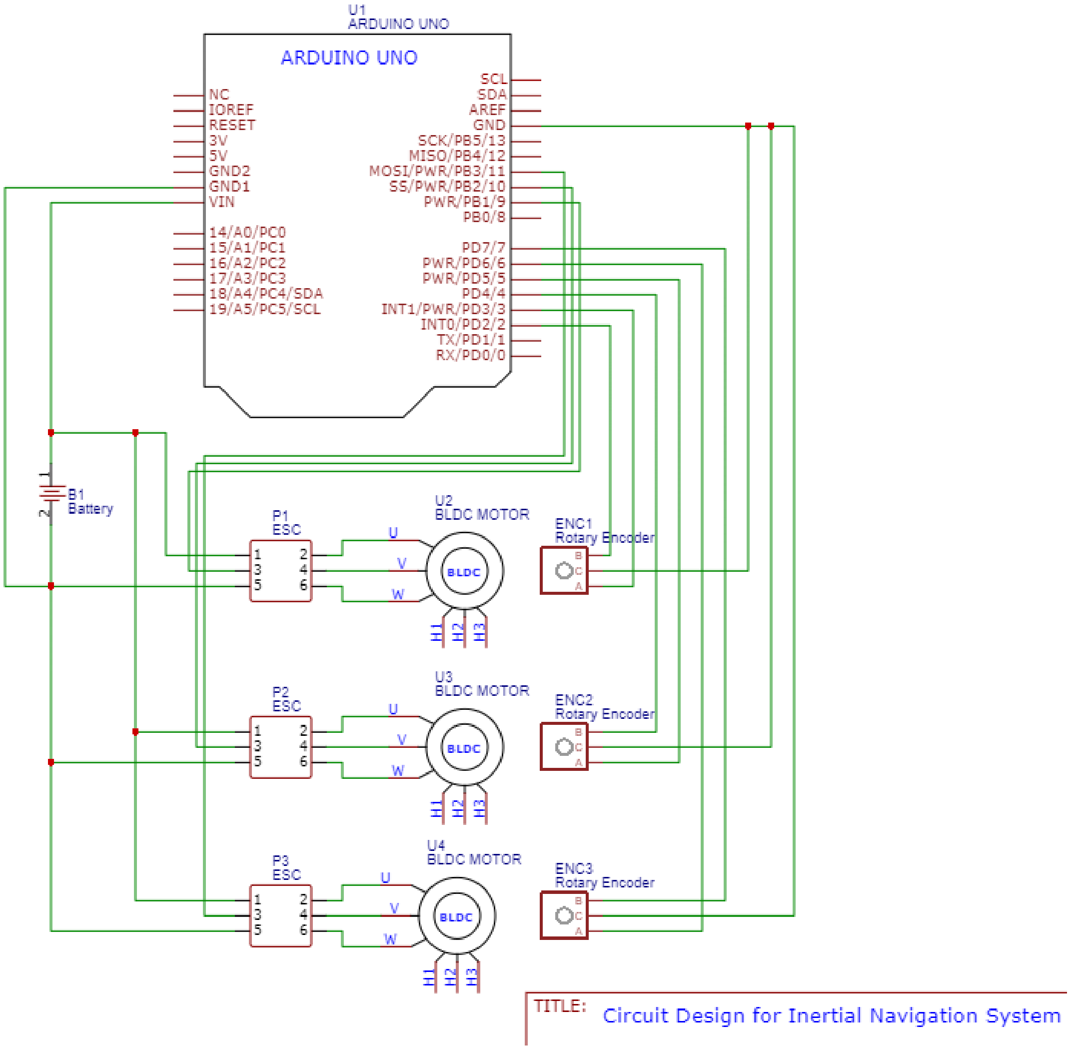

Fig. 2. Circuit design of the system

Figure 2 shows the inertial navigation system circuit design, in which an ESP8266 microcontroller serves as the central processing unit. Powered by a 2S 7.4V 2200mAh LiPo battery, the system integrates two 1000KV BLDC motors for (pitch, roll) and yaw axis rotations. Three 800 PPR rotary encoders are strategically positioned to capture high-resolution rotational data, providing accurate measurements of the device’s attitude and heading. The microcontroller processes the encoder signals, converting rotational movements into meaningful data. This information is then transmitted to the cloud through the ESP8266’s Internet connectivity, where a dedicated database (ThingSpeak) is established for comprehensive data storage and management.

Simultaneously, Electronic Speed Controllers (ESCs) are incorporated to regulate the RPM of the BLDC motors. These ESCs are directly interfaced with the PWM-capable pins of the ESP8266 microcontroller, facilitating precise control over the motors’ rotational speeds. The microcontroller dynamically adjusts the motor RPM based on processed data, ensuring real- time responsiveness of the attitude and heading indicators to changes in orientation.

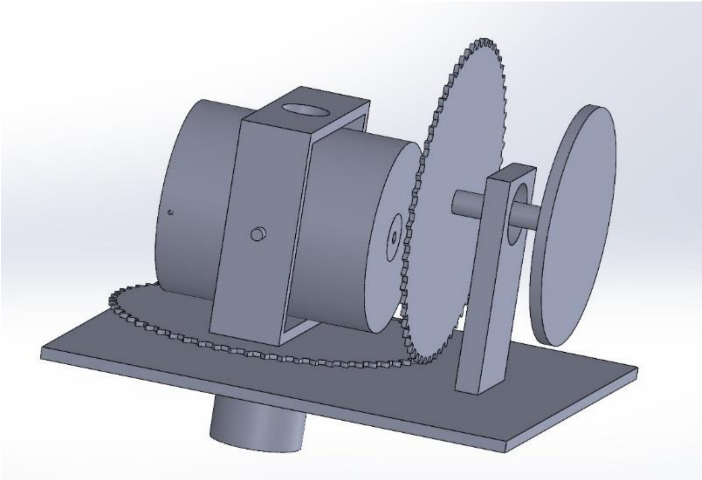

Fig. 3. Isometric view of the heading indicator

The combined design elements facilitate the collection of reliable and interpretable data accurately reflecting the INS's dynamic movements. This data serves as the cornerstone for training and evaluating the efficacy of the selected ML models in mitigating errors and enhancing navigation accuracy.

C. Evaluation Criteria

To assess the performance of each model, the Inertial Navigation System (INS) will undergo testing with diverse trajectory patterns, including the shape of an 8, a straight line, and a square trajectory. The algorithms' effectiveness will be measured by comparing their outputs with both raw data from the INS and reference data representing the actual trajectory. Utilizing established metrics for navigation accuracy, such as Root Mean Square Error (RMSE) and position drift, the research aims to discern the most optimal approach for integrating machine learning (ML) algorithms into INS systems.

D. Fabrication and Setup

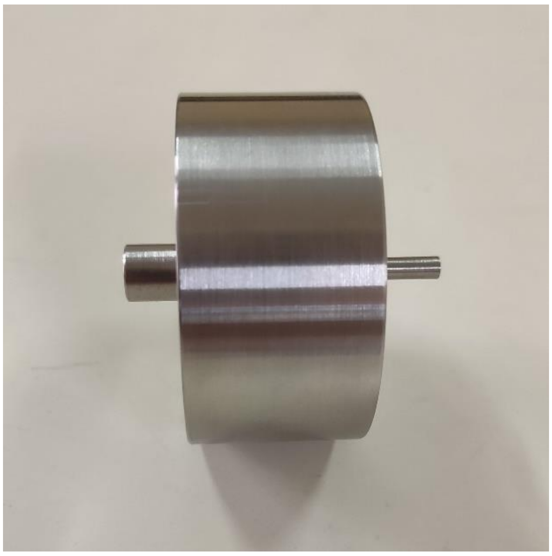

Fig. 4. Flywheel made from stainless steel

Figure 4 is the finished model of flywheel. This flywheel within the inertial navigation system was manufactured with precision using lathe cutting techniques from a solid steel block to ensure structural

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uniformity and durability, allowing for efficient storage of rotational energy. The overall structural composition of the system will feature a combination of materials, integrating 3D printed PLA for non-load bearing components due to its ease of 3D printing and cost- effectiveness. Simultaneously, load-bearing elements will be reinforced with aluminum, chosen for its favorable strength- to-weight ratio. This hybrid construction approach aims to achieve a balance between structural robustness and weight optimization, enhancing the system's overall performance and portability.

4. Results

A. Square Trajectory

In comparing Figure 5 to Figure 6, we spot clear differences in the recorded acceleration data from the Inertial Measurement Unit (IMU) within the Inertial Navigation System (INS). Figure 6 shows the raw acceleration values, giving us a basic understanding of the motion dynamics. However, Figure 7 reveals discrepancies between the recorded acceleration values and the ideal values, highlighting inaccuracies in traditional INS. Since the square trajectory is a 2D trajectory, we can observe no acceleration along the Z-axis.

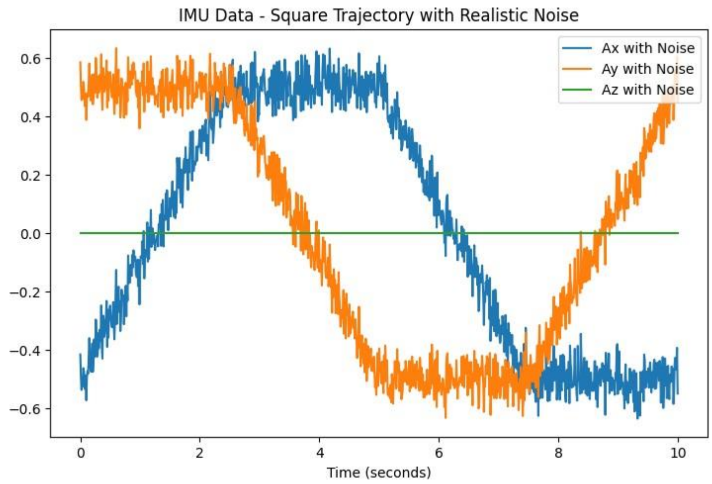

Fig. 5. Recorded acceleration values from the IMU within the INS

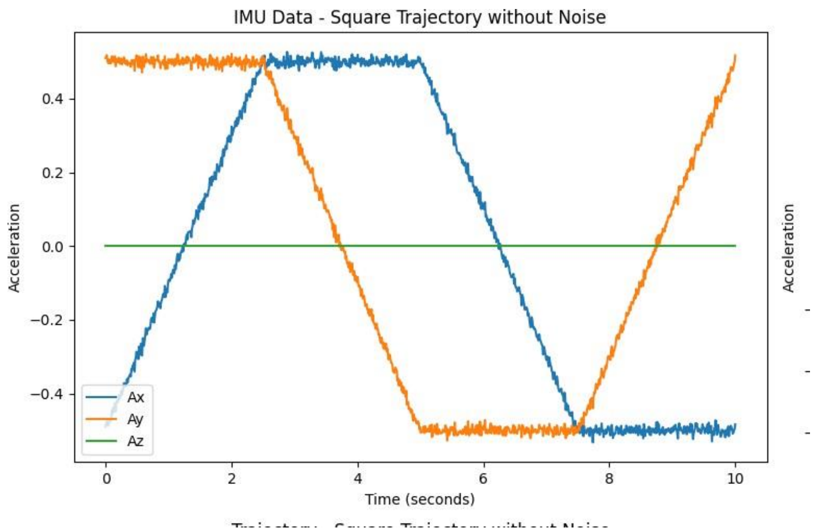

Fig. 6. Cleaned acceleration data using NEAT

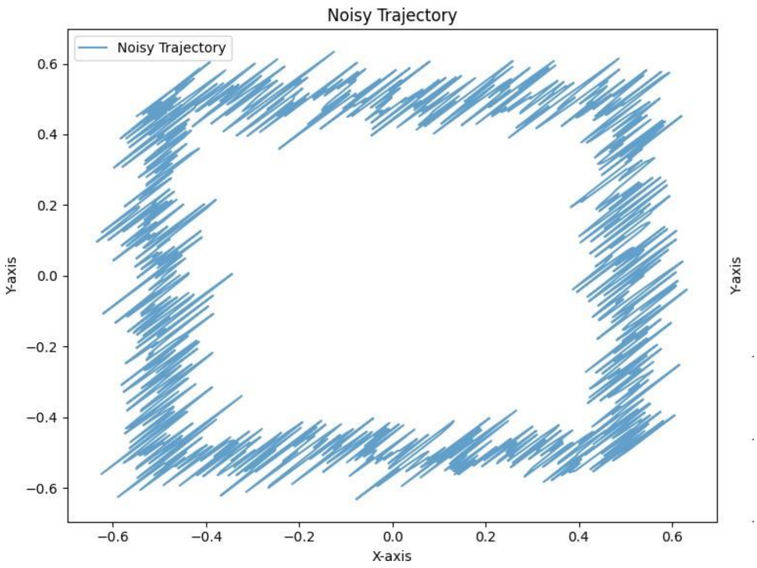

Fig. 7. Raw sensor data

To tackle these inaccuracies, we applied Neuro-Evolution of Augmented Topologies (NEAT) for trajectory refinement. Figures 7 and 8 illustrate the trajectory before and after cleaning, demonstrating a significant improvement in accuracy. Figure 7 displays the initial trajectory with errors, emphasizing inconsistencies, while Figure 8 showcases the refined trajectory. This underscores the efficacy of advanced techniques like NEAT in addressing limitations and enhancing inertial navigation system accuracy.
Notably, the Mean Squared Error on the Test Set was found to be 0.2235 during the ANN training, confirming the model's proficiency in improving trajectory precision.

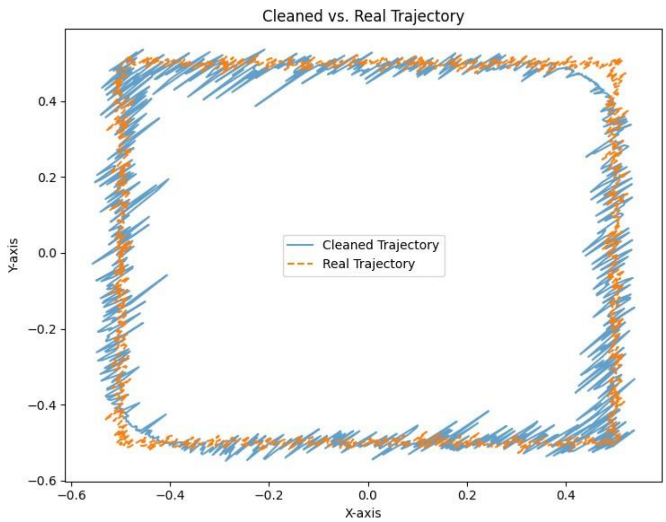

Fig. 8. Cleaned sensor data compared to actual reference data

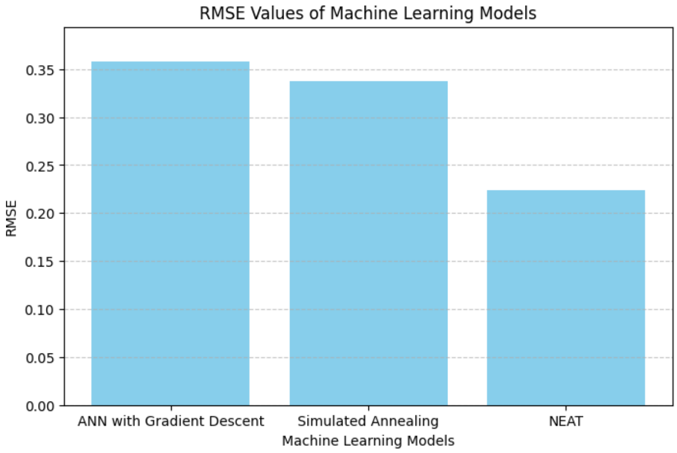

Fig. 9. Comparison of RMSE of different models

The performance of three different models for predicting system orientation and motion based on sensor data was evaluated. The Artificial Neural Network (ANN) with Gradient Descent achieved an RMSE of 0.3582, indicating moderate accuracy but with potential for improvement. Simulated Annealing yielded a slightly lower RMSE of 0.3371, implying enhanced accuracy through iterative optimization. However, NEAT (Neuro Evolution of Augmented Topologies) outperformed both with the lowest RMSE of 0.2235, showcasing superior accuracy due to its dynamic adjustment of neural net- work architectures through evolutionary algorithms, offering more efficient and adaptable models.

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6. References

1. Wen, K., Seow, C. K., Tan, S. Y. (2016). Inertial navigation system positioning error analysis and Crame´r-Rao lower bound. 2016 IEEE/ION Position, Location and Navigation Symposium (PLANS). doi:10.1109/plans.2016.7479704
2. E. Pukhov and H. I. Cohen, ”Novel Approach to Improve Performance of Inertial Navigation System Via Neural Network,” 2020 IEEE/ION Position, Location and Navigation Symposium (PLANS), Portland, OR, USA, 2020, pp. 746-754, doi: 10.1109/PLANS46316.2020.9110180.
3. A. I. Mourikis, N. Trawny, S. I. Roumeliotis, A. E. Johnson, A. Ansar, and L. Matthies, ”Vision-Aided Inertial Navigation for Spacecraft Entry, Descent, and Landing,” in IEEE Transactions on Robotics, vol. 25, no. 2, pp. 264-280, April 2009, doi: 10.1109/TRO.2009.2012342.