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Analysing the Composition and Trajectory of Asteroids using Machine Learning

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***Abstract* — Celestial mechanics plays a crucial role in understanding the motion of celestial bodies, such as asteroids and planets, in space. By studying the dynamics of celestial objects, scientists can gain insights into the formation, evolution, and behaviour of the solar system and beyond. The objective of this research paper is to explore numerical integration methods for predicting asteroid trajectories and studying the gravitational effects of planets. By leveraging numerical techniques, we aim to simulate the motion of asteroids accurately and investigate how planetary gravitation influences their trajectories. we will review the background literature on celestial mechanics and numerical integration methods, discuss the parameters used in celestial mechanics, explore the application of numerical methods in simulating celestial motion, and analyze the results of our simulations.**

Keywords : Asteroid Trajectory , Range-Kutta 4 Model , Celestial Body Movement , Asteroid Path Simulation

I. INTRODUCTION

Asteroids have long been a subject of fascination and concern for scientists and the general public alike. As we continue to explore space and search for ways to protect our planet from potential impacts, it becomes increasingly important to understand the composition and trajectory of these celestial bodies. In recently, machine learning techniques have emerged as a potent tool for analyzing asteroids, offering new insights and predictions about these enigmatic objects. Among all asteroids, NEAs have stepped into prominence because they are the easiest celestial bodies to reach from the Earth, while also representing a potential impact threat to our planet [1]. This paper will explore the various applications of machine learning in asteroid analysis, including the techniques used to analyze asteroid composition and predict their trajectories.

We will also examine the benefits and limitations of utilizing machine learning in this field, and consider the implications for future asteroid research. By exploring the intersection of machine learning and asteroid analysis, we hope to contribute to our understanding of these fascinating objects and their place in our universe.

The exploration of asteroids remnants from the early solar system, offer invaluable insights into the formation and evolution of our planetary neighborhood. Recent advancements in machine learning (ML) have opened new avenues for analysing the vast amount of data collected on these celestial bodies [3]. This literature survey focuses on the application of ML techniques in the analysis of asteroid composition and trajectory, emphasizing feature extraction, classification, and trajectory prediction methodologies.

Analysis of asteroid data, enabling the identification of characteristics that are most relevant for classification and trajectory prediction. Extracting photometric data from time-domain surveys represents a crucial step in elucidating the physical characteristics of asteroids, including their shape, spin, size, and surface composition.

Predicting the trajectory of asteroids is vital for assessing collision risks with Earth and planning space missions [6]. Machine learning techniques, including supervised quantum machine learning, have been explored for this purpose

Despite significant progress, challenges remain in the application of ML to asteroid analysis. The accuracy of classification and trajectory prediction models is limited by the quality and completeness of available data. Additionally, the dynamic nature of asteroid orbits, influenced by gravitational interactions and nongravitational forces, complicates trajectory prediction. Future research should focus on integrating more comprehensive datasets, including radar and thermal observations, to improve feature extraction and model accuracy. The development of novel ML algorithms capable of handling the complex dynamics of asteroid motion is also a promising direction for enhancing trajectory prediction capabilities.

II. LITERATURE SURVEY

2.1. Existing System

Asteroids are a common feature in our nightly observations of the sky and are frequently captured in the data collected by various astronomical surveys. Despite their ubiquitous presence, the focus of many surveys tends to be specialized, leading to the underutilization of their data for asteroid research[1]. and KMTNet [2] along with microlensing surveys like MOA, offer exceptional capabilities for determining the rotation period and orbital trajectory of asteroids. These surveys repeatedly observe a specific region of space throughout the night, enabling prolonged observations of asteroids within their field of view[3]. This extended observation period allows for the analysis of both the trajectory and the light emitted by the asteroids. Cordwell [4] has illustrated the effectiveness of extracting asteroid light curves from the data provided by MOA microlensing surveys.

Automated detection software has played a significant role in asteroid surveys since the early 1990s [5]. With advancements in computing power, alternative methods for identifying moving celestial objects, such as the shift and stack technique, have gained popularity. One notable advancement in recent years is the Pan-STARRS Moving Object Processing System (MOPS) [6]. Initially trained using simulated yet realistic asteroid data specific to Pan-STARRS telescopes, MOPS employs a sophisticated tree-based spatial linking algorithm [7]. This system identifies transient candidates not linked to known sources and further refines associations among these point sources. Notably, MOPS operates with celestial coordinates rather than imaging data, resulting in reduced computational costs.

Helio Linc [8] represents a further enhancement in efficiency compared to MOPS. It utilizes a heliocentric frame of reference and employs a clustering approach to group sources belonging to the same celestial object.

While deterministic methods have been effectively employed for asteroid detection, the application of deep learning in this domain is still in its early phases, possibly due to the scarcity of labeled data. Machine learning offers the advantage of learning directly from raw data, presenting a promising avenue for asteroid discovery within archival astronomical datasets.

Moghbi [9] demonstrated the successful utilization of convolutional and recurrent neural network architectures to streamline the vetting process for debris from long-period comets in CAMS data [10]. Another study employed neural networks to detect small solar system objects (SSOs) in simulated data for ESA's Euclid space telescope, leveraging transfer learning and retraining architectures from TensorFlow's Keras Applications to distinguish between asteroid images and common misidentifications like cosmic rays and stars.

Duev [11] introduced DeepStreaks to assist ZTF in identifying near-Earth asteroids, effectively reducing the number of candidate detections for review without compromising sensitivity. Rabeendran and Denneau [12] applied deep learning to ATLAS5 pipeline for near-Earth object detection, achieving a significant reduction in false positive detections and expediting follow-up observations..

Additionally, Duev [11] introduced Tails, training an object detector to identify comets based on their unique morphology, now integrated into ZTF's detection pipeline. Furthermore, Kruk [13] utilized deep learning to detect asteroid trails in archival data from the Hubble Space Telescope, employing composite images to enhance trail visibility and emphasizing the value of citizen science for data labeling and mining archival datasets for asteroids using deep learning tools.

2.2. Proposed System

Gathering data from astronomical observations, including spectral reflectance, visual light curves, and radar measurements, obtained from sources like NASA's Asteroid Data Archive and ground-based telescopes . If available, existing datasets containing labelled asteroid compositions and trajectories will be incorporated for training and validation.

All data would be cleaned and processed to address missing values, outliers, and inconsistencies in the procedural methods & feature engineering techniques may be employed to extract additional features from the raw data, potentially improving model performance.

Celestial mechanics, the study of motion under the influence of gravity, plays a crucial role in understanding the paths of asteroids. The Runge-Kutta 4 method, a numerical integration technique, becomes a valuable tool for tracing these trajectories.

Its motion can be described by a system of ordinary differential equations (ODEs) where its position (x,y) and velocity (vx,vy) are interrelated. These equations consider the gravitational influence of the Sun and potentially other celestial bodies. The Runge- Kutta 4 method tackles these ODEs in a step-by-step manner. Here's a glimpse into the process:

Initial Conditions: We begin by defining the initial state of the asteroid. This includes its initial position (x0, y0) and velocity (vx0, vy0), along with the gravitational constant and masses of relevant celestial bodies.

We subdivide the total travel time into small time intervals (dt). Each interval represents a small step in the asteroid's journey. At each time step, the method cleverly calculates four intermediate values for the position and velocity changes (kx, ky, kvx, kvy) based on the current state and the governing equations.

The final update for each time step is obtained by averaging these intermediate values. This averaged change is then added to the current position and velocity to arrive at the asteroid's state at the next time step. This process of calculating intermediate values, averaging, and updating the state is repeated for each time step, effectively following the asteroid's path across time.

The Runge-Kutta 4 method builds a numerical representation of the asteroid's trajectory. This allows us to visualize its path, predict its future location, and assess potential collision risks.

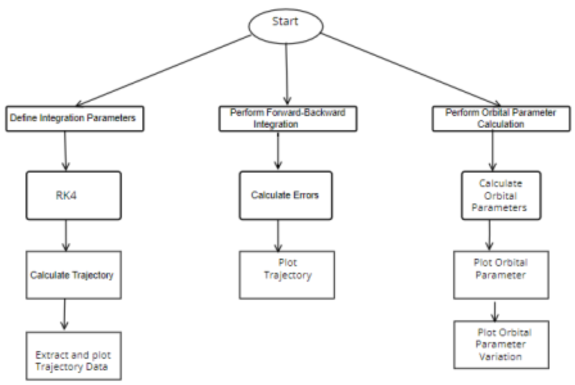


Fig 1.1 Backend work flow

III. METHODOLOGY

It utilizes a combination of numerical methods and celestial mechanics principles to simulate the motion of an asteroid in space, considering the gravitational influences of multiple planets. Here's the methodology employed:

Step 1: User Input: The user provides input regarding the initial conditions of the simulation, including the date of the start, duration, step size, integration method, and asteroid parameters such as mass and orbit.

Step 2: Integration Parameters: Based on user input, the simulation defines the integration parameters, including the start date, duration, and step size. These parameters determine the granularity and accuracy of the simulation.

Step 3: Planetary Influences: The user selects planets whose gravitational effects will be considered in the simulation. These planets contribute perturbations to the trajectory of the asteroid.

3.1. Integration Methods:

1. Runge - Kutta 4 (RK4): This numerical integration method is employed to approximate the trajectory of the asteroid overtime. It calculates the position and velocity of the asteroid at discrete time steps based on the gravitational forces acting on it.

   $y_1 = y_0 + (1/6)\,(k_1 + 2k_2 + 2k_3 + k_4)$ [14]

2. Forward-Backward Integration: Optional method that involves running the RK4 integration forward in time and then backward from the final state. It helps assess the accuracy of the integration by comparing the initial and final states.

3. The simulation calculates the orbital parameters of the asteroid, which encompass the semi-major axes, eccentricity, and inclination, derived from its position and velocity vectors. The results of the simulation are visualized using 3D plots, showing the trajectories of the asteroid and selected planets over time. Additional plots display orbital parameters variations.

4. Error Analysis: If forward-backward integration is performed, the simulation calculates errors between the initial and final states, providing insights into the accuracy of the integration. Users can adjust the simulation parameters based on the

results and rerun the simulation to refine the trajectory prediction.

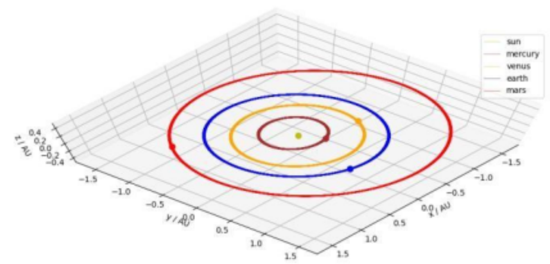


Fig 1.2 (Orbits inner planets, for 250 years)

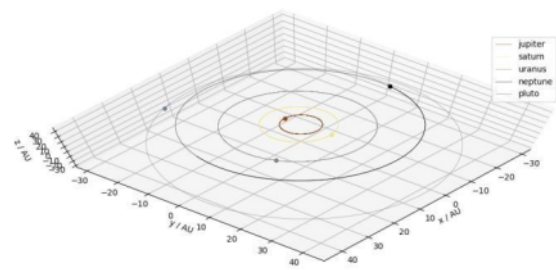


Fig 1.3 (Orbits outer planets, for 250 years)

3.2. Parameters Used :

Step Size : The "step" in the Integration parameters box refers to the time step used in the simulation. It determines how frequently the simulation calculates the position and velocity of the asteroid as it moves through space.
A smaller time step means the simulation calculates these values more frequently, resulting in a more accurate representation of the asteroid's trajectory. However, using a smaller time step also increases the computational load and may require more processing time to complete the simulation.

Values of the planets in the project likely refer to various parameters that define each planet's orbit around the Sun. These parameters include:

1. Mass: The mass of the planet, which affects its gravitational influence on other objects.
2. Semi-major axis: The average distance between the planet and the Sun, which defines the size of the planet's orbit.
3. Inclination: The angle between the plane of the planet's orbit and the plane of the ecliptic (the plane of Earth's orbit around the Sun).
4. Eccentricity: A measure of how elliptical (noncircular) the planet's orbit is.
5. Longitude of Ascending Node: It denotes the angle between the reference direction, typically the vernal equinox, and the location where a planet's orbit intersects the ecliptic plane, tracing from the south to the north.
6. Argument of Periapsis: This angle is the measurement, within the plane of the planet's orbit, between the ascending node and the periapsis, which marks the closest point of the orbit to the Sun.
7. Mean Anomaly: The angular distance along the planet's orbit from the periapsis at a specific point in time.
8. Epoch: The reference time from which the mean anomaly is measured, often set to J2000.0 (January 1, 2000, 12:00 TT).

Parameters used for Asteroid Trajectory Calculation

- Mass
- Semi-major axis
- Eccentricity
- Inclination
- Longitude of the ascending node
- Argument of periapsis
- Mean anomaly

Parameters used for Jupiter Trajectory Calculation

- Semi-major axis
- Eccentricity
- Inclination
- Longitude of the ascending node
- Argument of periapsis
- Mean anomaly

3.3 Initialization :

1. Constants: m_sun (mass of the Sun) and G (gravitational constant) are defined.
2. Planets: The planet class is defined to represent celestial bodies. Instances of this class are created for the Sun and Jupiter.
3. Integration Parameters: tf (final time), ti (initial time), step (time step), and time (array of time points) are defined.
4. Initial Conditions: Initial state of the asteroid (init_state) is calculated using its orbital elements at the initial time.

3.4 Orbit Motion Calculation :

i). Calculates the accelerations of the asteroid due gravitational forces from other celestial bodies.

Formula:

Newton's law of universal gravitation:

$$F = G.m1.m2/r^2$$

Purpose: Computes the acceleration components of the asteroid to simulate its motion under the influence of gravitational forces.

ii) RK4 Methods:
Implements the Runge-Kutta 4 integration method to numerically solve the equations of motion for the asteroid.

1st Order Runge-Kutta method

$$y_1 = y_0 + hf(x_0, y_0) = y_0 + hy'_0 \quad [14]$$

3.5 Orbital Parameter Calculation:

i) orbitalparamvector : Calculates the position vector of the celestial body based on its orbital parameters (semi-major axis, eccentricity, etc.).

Formula:

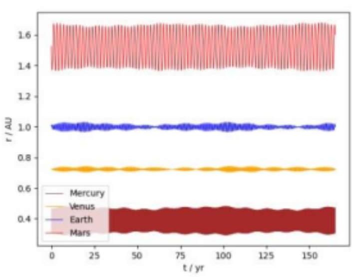
$$X=a.\cos(w.t)$$
$$Y=a.\sin(w.t)$$
$$Z=0$$

Purpose: Provides the position of the celestial body in its orbital plane at a given time.

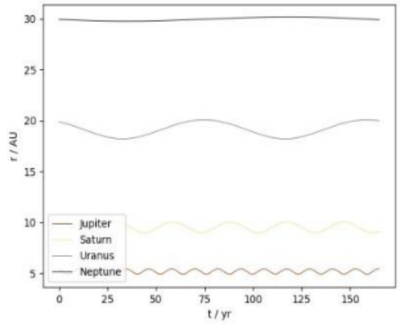
ii) completeOrbitalElemVector : Calculates the position and velocity vectors of the celestial body based on its orbital elements using Kepler's equation and coordinate transformations.

Kepler's Equation: $M=E-e.\sin(E)$ [15]

Purpose: Determines the position and velocity vectors of the celestial body in three-dimensional space at a given time, considering orbital eccentricity and inclination.



(a) Inner planets



(b) Outer planets

Fig 1.4 Distance to center of gravity, using Runge-Kutta-Fehlberg method

When examining the global error of the RKF method, the initial distinction between the methods becomes evident, as the global errors of the RKF method are an order of magnitude smaller than those of the RK4 method.

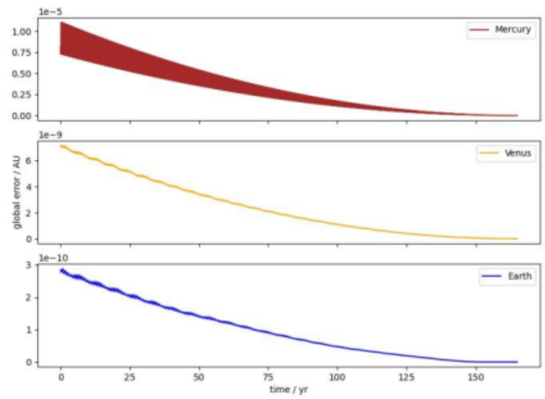


Fig 1.5 Global error, using Runge-Kutta-Fehlberg method

IV. EXPECTED OUTCOMES

This research investigates the influence of three key parameters - eccentricity, inclination, and semi-major axis - on asteroid trajectories. Eccentricity describes the orbit's shape, with a value of 0 indicating a perfect circle and values closer to 1 signifying a more elliptical path. Inclination reveals the tilt of the orbit relative to the plane of the solar system. Finally, the semi-major axis defines the asteroid's average distance from the Sun.

By analyzing these parameters, the study aims to:

- Classify Asteroid Groups: Asteroids with similar eccentricity and inclination values might belong to the same collisional family or share a common origin.

- Predict Potential Collisions: Asteroids with highly eccentric orbits that cross Earth's path pose a potential collision threat.

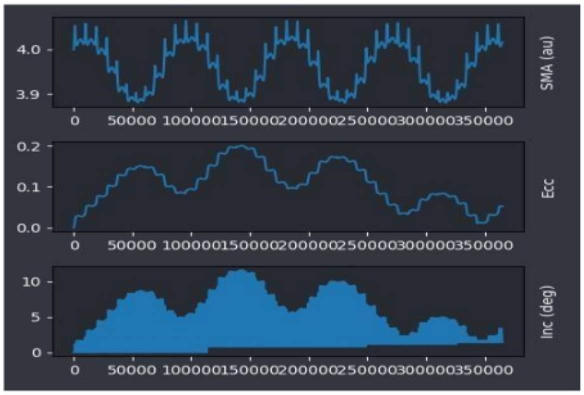


Fig 1.6 Outcome Result (Ecc, Inc, SMAxis)

This research can help identify such objects and assess their risk.

Optimize Spacecraft Missions: Understanding an asteroid's trajectory through these parameters allows for mission planning with efficient fuel usage and encounter strategies. The expected outcome is a clearer understanding of how these parameters governs asteroid movement. This knowledge can contribute to asteroid classification, risk assessment, and the design of future space missions, ultimately fostering a deeper comprehension of our solar system's dynamics.

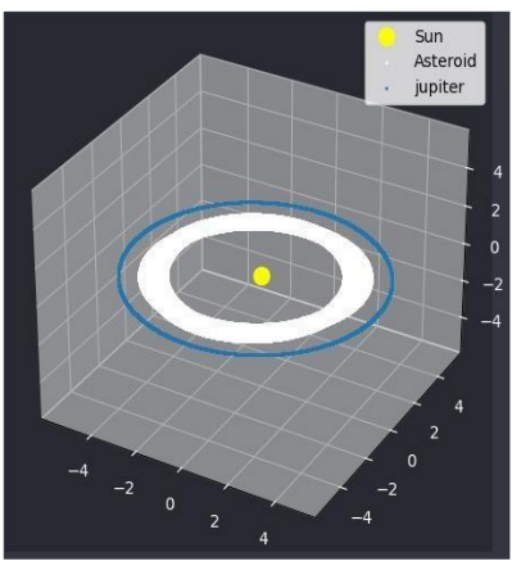


Fig 1.7 Asteroid Trajectory Display

V. FUTURE SCOPE

Extension to Multiple Planets: The current simulation focuses on the gravitational influence of Jupiter alone. Future research could extend this study to include the gravitational effects of other planets in the solar system, such as Saturn, Mars, and Venus. This extension would provide a more comprehensive understanding of the complex interactions between celestial bodies.

Integration of Perturbation Effects: While the current simulation considers only the central gravitational force of Jupiter, future work could incorporate additional perturbation effects, such as gravitational interactions with other asteroids or non-uniformities in the gravitational field. Including these perturbations would lead to a more accurate representation of the asteroid's trajectory.

Enhanced Numerical Methods: Investigating advanced numerical integration methods beyond the RK4 scheme could improve the accuracy and efficiency of trajectory simulations. Techniques such as symplectic integrators or adaptive stepsize control could be explored to enhance the computational efficiency and stability of the simulations.

VI. CONCLUSION

Implementing Runge-Kutta 4 method to enhance the accuracy of asteroid trajectory simulations. This powerful numerical technique surpasses simpler methods by incorporating multiple evaluations per step, reducing errors and yielding a more realistic depiction of the asteroid's path.

By incorporating the effects of eccentricity, inclination, and semi-major axis, the Runge-Kutta 4 method provides a robust framework for modeling asteroid motion. This refined approach promises to significantly improve our understanding of asteroid movement within our solar system.

The anticipated outcome is a more precise characterization of asteroid trajectories. This advancement will bolster our ability to classify asteroid groups, assess collision risks, and optimize spacecraft missions, paving the way for a new era of asteroid exploration and celestial discovery.

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