Analyzing 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 behavior 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 recent years, machine learning techniques have emerged as a powerful tool for asteroid analysis, offering new insights and predictions about these enigmatic objects. 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, provides invaluable insights into the formation and evolution of our planetary neighborhood . Recent advancements in machine learning (ML) have opened new avenues for analyzing the vast amount of data collected on these celestial bodies. 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. The extraction of photometric data from time-domain surveys is a significant step in determining physical characteristics such as shape, spin, size, and surface composition of asteroids .

Predicting the trajectory of asteroids is vital for assessing collision risks with Earth and planning space missions. 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 part of the landscape of our night sky and appear in the imaging data of most astronomical surveys. However, as most surveys have a specialized purpose, their data is rarely mined for asteroids.

Microlensing surveys like MOA [1] and KMTNet [2] are particularly good for determining the rotation period and orbital trajectory of asteroids because there survey a given region of space several times each night (Gould and Yee [3]). This means that asteroids could spend several nights in the field of view of the telescope, giving us the opportunity to both observe their trajectory and analyse the light gathered from them. Cordwell [4] demonstrates the efficacy of extracting asteroids light curves from the MOA microlensing data.

Automated detection software has been part of surveys dedicated to discovering asteroids since the early 90s [5] .With improved computing power, other techniques for detecting moving astronomical sources such as shift and stack have also proven popular. In recent years, a leader in the field is the Pan-STARRS Moving Object Processing System [6] or MOPS. Initially trained with simulated but realistic asteroid data for the PanSTARRS telescopes, it takes transient candidates not associated with a known source and uses a complex treebased spatial linking algorithm [7] to further parse and form associations between these point sources. MOPS does not work with imaging data but rather celestial coordinates, which reduces the computational cost.

HeliolinC [8] further improves on MOPS' efficiency with an approach that combines working with a heliocentric frame of reference and clustering sources that belong to the same object.

While these and other deterministic approaches have been successfully utilized for asteroid detection, applications of deep learning in the field remain in the early stages, potentially because of the lack of labelled data. Machine learning offers the benefit of being able to learn representations directly from the raw data, making it a potentially valuable tool for asteroid discovery in archival astronomical data. The works that do apply machine leaning techniques note the benefits, particularly with greatly reducing the amount of data that must be examined by an astronomer, as we see next.

Zoghbi [9] successfully applied both convolutional and recurrent architectures to reduce the amount of data to be vetted by astronomers looking for debris from longperiod comets in the CAMS data. [10] Neural networks was assigned for the task of detecting small solar system objects (SSO) in data simulated for the ESA's Euclid space telescope.

They successfully used transfer learning and retrained three architectures from TensorFlow's Keras Applications to distinguish between postage stamp cutout images of asteroids and objects commonly mistaken for asteroids like cosmic rays, stars, and galaxies.

Duev [11] introduced DeepStreaks to aid in the ZTF's quest for the discovery of near-Earth asteroids, which resemble streaks in the observations. Their model significantly reduced the number of candidate detections that had to be reviewed without sacrificing the detection sensitivity. Rabeendran and Denneau [12] applied deep learning to the ATLAS5 pipeline looking for near-Earth objects. It was successful in catching nearly 90% of the false positive detections, thus greatly speeding up the process of followup observations.

Duev [11] introduced Tails, which involved training an object detector to discover comets based on their distinctive morphology and it now forms a part of the ZTF's detection pipeline. Finally, Kruk [13] used deep learning to hunt for asteroid trails in archival data from the Hubble space telescope . They used composite HST images to make the asteroids trails longer and thus easier to detect. Their research also demonstrates the merits of citizen science for labelling the data and of mining archival data for asteroids with a deep learningbased toolkit.

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 labeled 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 methoda & 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.

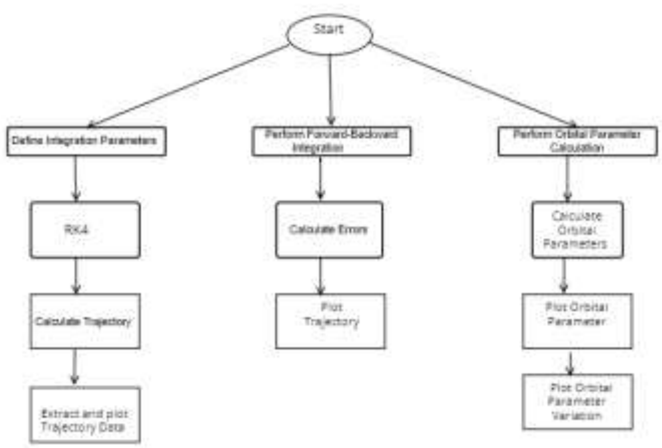


Fig 1.1 Backend work flow

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.

   $y_1 = y_0 + (⅙) (k_1 + 2k_2 + 2k_3 + k_4)$

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 computes the orbital parameters of the asteroid, including semi-major axis, eccentricity, and inclination, based on 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.

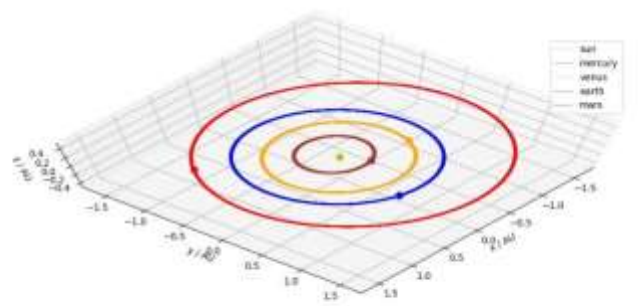


Fig 1.2 (Orbits inner planets, for 250 years)

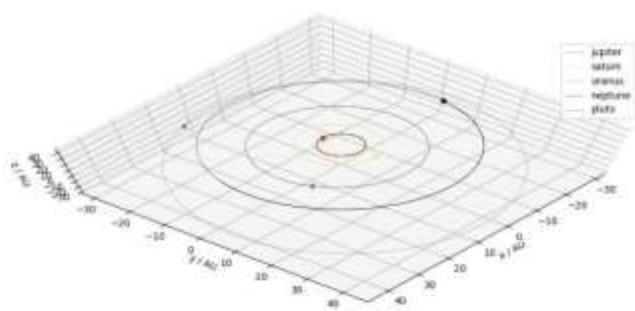


Fig 1.3 (Orbits outer planets, for 250 years)

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: The angle between the reference direction (such as the vernal equinox) and the point where the planet's orbit crosses the ecliptic plane from south to north.
6. Argument of Periapsis: The angle between the ascending node and the periapsis (the point of closest approach to the Sun) measured in the plane of the planet's orbit.
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 Intialization :

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

$$y_1 = y_0 + hf(x_0, y_0) = y_0 + hy'_0$$

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:

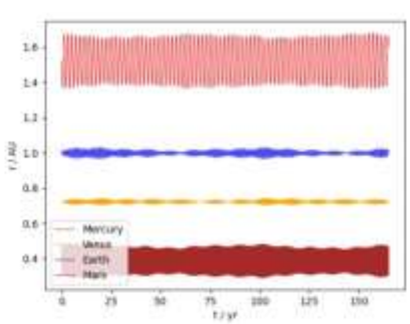
$$X=a.\cos(w.t)$$
$$Y=a.\sin(w.t)$$
$$Z=0$$

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

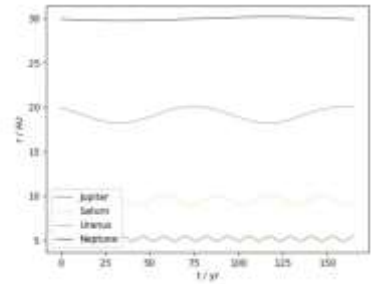
ii) completeOrbitalElemVector : Calculates the position and velocity vectors of the celestial body based on its orbital elements using Kepler's equation and coordinate transformations.

Kepler's Equation: $M=E- e\sin(E)$

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 looking at the global error of the RKF method, first difference between the methods is noticeable, because the global errors of the RKF method are one magnitude smaller than the global errors of the RK4 method

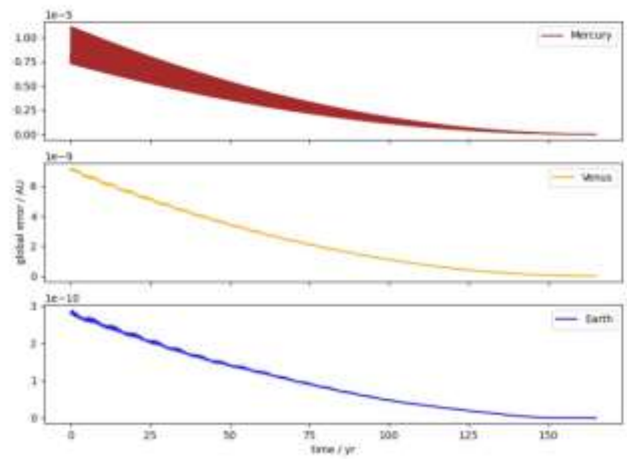


Fig 1.5 Global error, using Runge-Kutta-Fehlberg method

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.

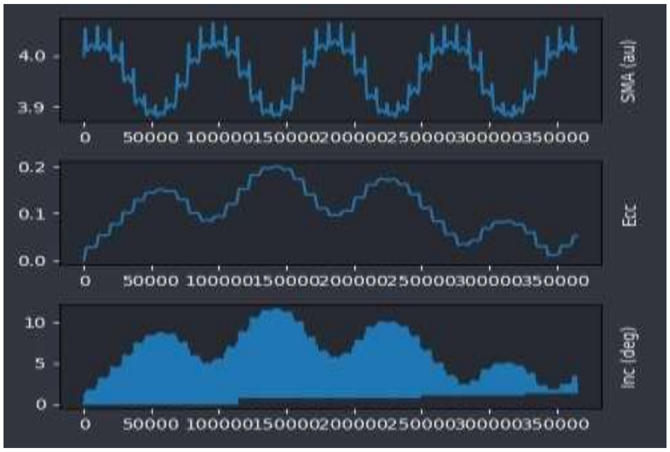


Fig 1.6 Outcome Result (Ecc ,Inc ,SMAxis)

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 govern 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.

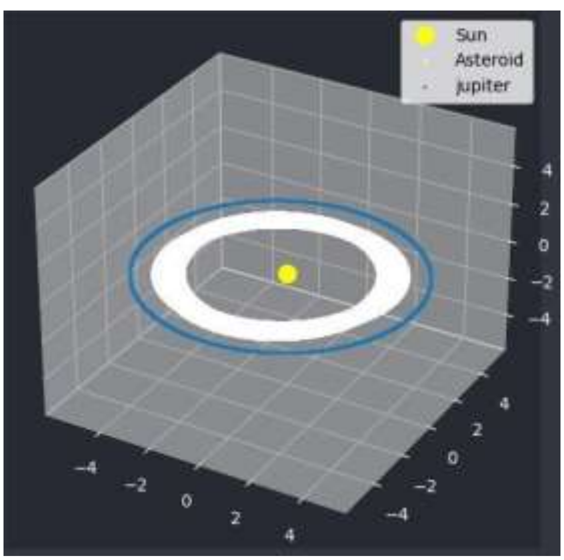


Fig 1.7 Asteroid Trajectory Display

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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