Internship in ESA's Advanced Concepts Team
On
Poincare Maps and Chaos Classification / Regression

European Space Research and Technology Centre
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Topic description

Poincaré maps are representations of continuous dynamical systems in a lower-dimensional subspace called the Poincaré section. They are typically used to produce discrete estimates of dynamical systems in order to analyze them more efficiently and extract relevant information about the stability of the system and locus of periodic and quasi-periodic motion [1]. A common application for such maps in astrodynamics is the search for stable and unstable regions of motion in non-Keplerian dynamical systems such as the Circular Restricted Three-body Problem [2].

Machine learning techniques could allow for efficient dynamical system property identification and phase-space classification by training neural networks to learn essential properties of dynamical systems from datasets of Poincaré maps in 2D and higher dimensions. Recent studies have already demonstrated the capability of "reservoir computing" techniques to predict the evolution of chaotic systems and derivate Lyapunov exponents from discrete datasets [3-5], but to our knowledge no prediction or classification have been made to this day from lower-dimensional subspaces such as Poincaré maps.

Candidate's tasks

- Pick the most promising system properties extractable from Poincaré maps for dynamical system identification (e.g. chaos indicator, system integrability, orbit stability domains ...).
- Define a learning strategy: is it possible to learn across different sets of dynamical systems?
- Create training datasets, starting with a well-known problem and a 2-D map (e.g. swinging Atwood's machine [6]).
- Design neural networks to compute system properties and classify phase-space regions from Poincaré maps.
- Train, test and iterate.
- Publish implementation, results and training sets as open source code.
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The ideal candidate

- Background in machine learning, applied mathematics, dynamical systems theory.
- Master student in computer science, applied mathematics or equivalent.
- Good proficiency in Python language.
- Experience with open source contributions.

References

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[2] - Ross, S. D., Koon, W. S., Lo, M. W., & Marsden, J. E. (2006). Dynamical Systems, the Three-Body Problem and Space Mission Design. ISBN: 978-0-615-24095-4
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