Using two-factor similarity scoring functions to quantify and optimize the morphological similarity of models of interacting galaxies

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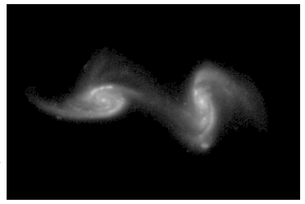
Abstract

Gravitational n-body models can be used to simulate the dynamical evolution of colliding galaxies. Given observational data in the form of images of the galaxies, it is possible to estimate the true values of the various dynamical parameters through the careful application of optimization methods. However, the optimizing of such n-body models can be quite difficult for a number of reasons. First, full n-body codes are computationally expensive and the application of any optimization method requires many model runs. Second, due to the dimensionality and non-linearity of the system, the parameter space that must be explored is very complex. To address these challenges, we developed multi-factor similarity scoring functions which are able to able to accurately perform morphological comparisons between model and target images. Using these functions, we apply a novel adaptive kernel mixing strategy which can be applied in both stochastic optimization and Markov chain Monte Carlo contexts. Using simulated models with known parameters as a surrogate for actual observational data, we test our fitness and optimization techniques for robustness, accuracy, and convergence.

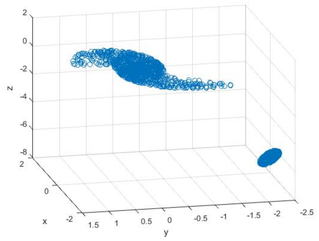
1 Introduction

Terminology:



- Morphology: a galaxy's shape
- Dynamical history: its trajectory
- Interaction: an event where close passage of two galaxies causes tidal disturbances in their morphology
- Tidal features: distortions in the original morphology of a galaxy due to an interaction

Simulation of interacting galaxies with *SPAM* code:



- Uses restricted 3-body scheme for fast runtime
- Galaxies represented as a center of mass surrounded by a cloud of massless particles
- One galaxy (the primary) is held fixed at the origin while the other (secondary) orbits around it
- Takes 14 dynamical parameters as input: $x, y, z, v_x, v_y, v_z, m_p, m_s, \rho_r, \rho_s, \phi_p, \phi_s, \theta_p, \theta_s$

Goals:

- Fit models of interacting galaxies to a given observational target image
- Analyze the relationship between morphology and dynamical history
- Estimate true values of dynamical parameters

Challenges:

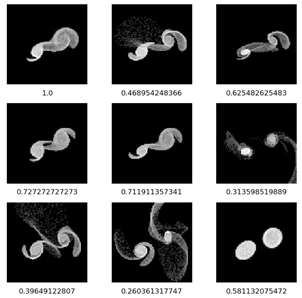
- Complex, degenerate parameter space
- Overabundance of poor models
- How to quantify similarity b/t model and target images

Solutions:

- Two-factor similarity scoring methods
- An adaptive kernel mixing strategy applicable in stochastic optimization or Markov chain Monte Carlo contexts

2 Methods

Using any single score as a metric for similarity leads to an unintuitive ranking of model quality:



Images created by applying a 2D histogram (x, y) to the particle positions output by SPAM using logarithmic scaling.

The images to the right display some of the different morphologies which can immerge from tidal interactions. The numbers under each image are a calculation of the repsective image's similarity (using a particular machine scoring technique) with the top right image, which serves as an artificial target image. As can be seen, though the numbers do a reasonably good job of distinguishing good matches, it fails in several places. For instance, the bottom right image is clearly less similar to the target than the top center image, and yet it's score is higher.

Challenges to similarity scoring:

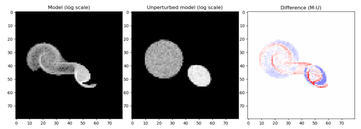
- Models with a small degree of tidal distortion are biased too high
- Models which have significant distortion tend to be scored too low if the distortions occur in different places from the target
- The majority of models are low-distortion
- Due to symmetries in the geometry of the system, disparate parameter sets can lead to nearly identical model images (degeneracy).

Solution: quantify the amount of tidal distortion and include this as another term in our scoring function

- TM score: comparison of the target and model images
- MU score: comparison of the model and "unperturbed model" images

What is an unperturbed model?

Perfectly undistorted disk galaxies are translated to the final simulation position in order to see where interactions create create distortions



Similarity score: flattened binary intensity correlation

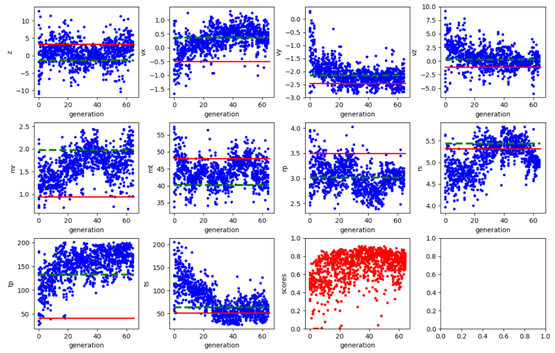
$$F_1(T, M) = \frac{\mathrm{Cov}(T_b^{1D}, M_b^{1D})}{\sqrt{\mathrm{Var}(T_b^{1D})\mathrm{Var}(M_b^{1D})}}$$

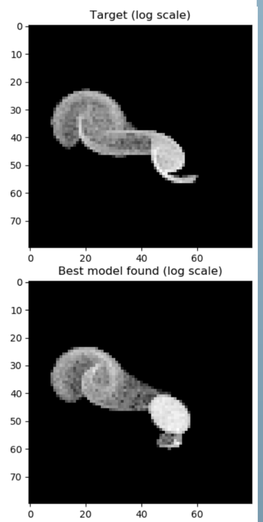
$$F_2(T, M) = F_1(T, M) \cdot \exp\left(-\frac{1}{2} \frac{\left(F_1(M, U_M) - F_1(T, U_T)\right)^2}{\sigma^2} \right)$$

Optimization technique: genetic algorithm (GA) Uses an population of candidate solutions to the problem which improve over time via a simulated evolutionary process (define the size of population N_{pop} and number of generations N_{gen})

3 Results

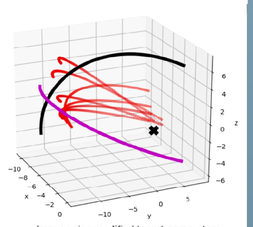
Below: convergence results for a single GA run. Blue points: solutions tested by the GA. Red lines: true parameter values for target. Dashed green lines: parameter values for the best model found. Right: the target image and best model image found by the GA (similarity score of 0.91/1.00).

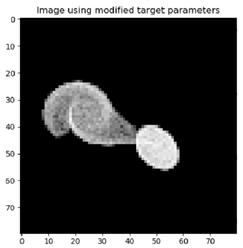




Analysis:

Comparing the target image and best model image, we can see that our GA was able to match the morphology of the primary galaxy quite well, but failed to capture the tidal tails of the secondary. Since the orientation of the secondary galaxy is decoupled from the orbital trajectory and the orientation of the primary galaxy, we can produce a model that agrees with most of the major features of the target but gets the orientation (and tidal features) of the secondary galaxy wrong. To the right, we have an image of the orbit of the target (black line), several of the best found solutions (red lines), and a modified target where we have inverted the trajectory of the secondary galaxy (magenta line). This model reproduces the tidal features of the primary galaxy, but not the secondary galaxy. Models like these will inevitably be scored highly, creating a false maximum.





4 Conclusions

The combination of our patricular similarity scores and our chosen optimization scheme leads to a high degree of morphological convergence. However, due to morphological degeneracies inherent within the system, multiple disparate regions of parameter space lead to very similar images, thus causing convergence of several parameters to incorrect values. To combat this, we plan to investigate the symmetries within the system which lead to this degeneracy and implement measures in the optimization scheme to account for them.