Determination of Orbital Parameters of Interacting Galaxies Using Evolution Strategies

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Abstract. In this work we apply Evolution Strategies as a method to find the orbital parameters of a pair of interacting galaxies using a single photometric image. Finding the orbital parameters that best match the image is done by posing it as an optimization problem and solving it using Evolution Strategies. Orbital parameters are estimated using position data from the image only, but in some cases is possible to use velocity data. As working directly with galaxies is unfeasible, we have used single simulations for modeling the system of galaxies, we present experimental results using synthetic data instead of a real image, showing that Evolution Strategies can determine orbital parameters of interacting galaxies very accurately.

1 Introduction

Evolution Strategies (ES) attempt to apply the idea of biological evolutionary process to optimization tasks; finding orbital elements of a pair of interacting galaxies can be seen as an optimization problem if any adaptation process is done, i.e. we need to find orbital elements that maximize (or minimize) our fitness function based on comparison between images. We choose ES instead of Genetic Algorithm because ES are better suited for working with continuous spaces, where the problem of finding orbital elements falls, due to the physical quantities involved. Another reason to work with ES is that in the framework of interchange of ideas between different scientific fields (Astrophysics and Machine Learning) we try to introduce unexplored techniques to Astrophysics; ES have not been used before in Astrophysics to the best of our knowledge, this leads to expanding the application field of ES.

Our proposed solution to this problem follows the basic algorithm for ES [8], with only small changes in the use of the genetic operators. We use cross-over, mutation and average as genetic operators to generate new populations in ES; the selection process is $(\mu + \lambda)$, where the μ best fit individuals of the union of parents and children are selected and we use dynamic mutation, applying a variable mutation step to all individuals, depending on if they are near or far from the solution. A vector that contains a set of orbital parameters represents each individual in the ES population; the structure and details are showed in section 4.

In Astrophysics, the study of galactic science is essential to understand an extraordinary set of fundamental subjects, from star formation to cosmological questions; galaxies are the fundamental blocks in the construction of the Universe. In particular, pairs of interacting galaxies are very important because almost every galaxy in the Universe has been created or shaped by means of an interaction or even by mergers between galaxies.

In the study of galactic dynamics there are some effects that are especially useful: when two galaxies interact, many different structures can be produced, and in some cases the galactic discs can be destroyed. Some examples of possible structures are: bridges and tails, spiral structures, bars, rings, lenses, deformations and bulges [2]. However, observations are not enough to understand the dynamical nature of the galaxies. Due to the enormous time scales involved in galactic interaction, with direct observations it is only possible to obtain single snapshots. Fortunately, such snapshots give some information due to the deformations produced by gravitational forces between galaxies; in addition to position data, obtained directly from the image, the radial velocity field can be measured by means of a spectrograph, also, it is possible to do an estimation of the mass of the galaxies, the number of stars and the time of interaction. On the other hand, and due to the last point, simulations are very important tools to study galaxies and are essential as a complement to direct observations.

Finally, in order to understand completely the dynamics of an interacting system of galaxies it is equally important to know the parameters of the relative orbit of the two galaxies. Such parameters define the geometrical orbits of both galaxies and allow knowing the position of the galaxies, and their structures, in any point of the time.

Currently, we have obtained results for synthetic data, i.e. we generate artificial images using the simulator program and save the image, its mass and velocity distributions and its parameters to compare later with the results obtained from ES.

The organization of the remainder of this paper is as follows: Section 2 contains a description of the problem, the method of solution is presented in Sect. 3, the results are given in Sect. 4 and the conclusions are presented in Sect. 5.

2 The Problem

The problem to be solved is the following: Given an image, obtained from photometric observations, and in some cases data concerning velocity obtained from spectroscopic observations, of a pair of interacting galaxies, we will find the set of orbital parameters that best match it.

Orbital parameters to be learned by the algorithm are: a (semi-major axis), e (eccentricity), i (inclination), Ω (longitude of the ascending node), ω (the argument of the pericentron) and τ (the time of the pericentre passage) [1,5].

3 Description of the Method

Basically, the solution process can be divided in two blocks: estimation of the orbital parameters using ES; and running a simulator program for each set of parameters, or individual.

Fig. 1 shows the general procedure to solve the problem. The first block represents the estimation of the parameters by ES; the next block represents the program simulator and the last is the comparison module, where the fitness function is evaluated for each individual and indicates if an individual has reached the threshold fitness or if the maximum number or generations has been done.

The following two subsections describe how ES were used for searching the orbital parameters, and explain individual simulations.

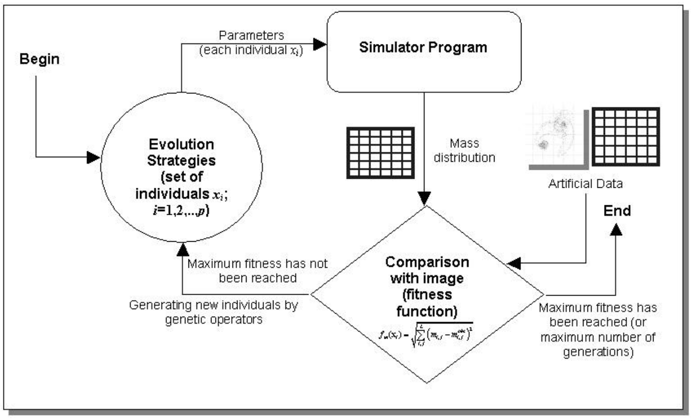


Fig. 1. Schematic description of the solution process

3.1 Evolution Strategies

At the start of each run, a population of p individuals is randomly created using a uniform distribution, in all the experiments for this work p is equal to 50. An individual in the population has the following structure:

$$\begin{aligned} op_i &= \langle m_1,\, m_2,\, \Delta z,\, s_1,\, s_2 \rangle \\ sp_i &= \langle \sigma_1,\, \sigma_2,\, \sigma_3,\, P_1,\, P_2 \rangle \ i = 1{,}2{,}\ldots{,}p \end{aligned}$$

Where op is the object parameter vector and sp is the strategy parameter vector used to modify the object vector in the mutation process.

In the vector op the parameters are: m_1, mass of galaxy 1; m_2, mass of galaxy 2; Δz, separation in the line of sight ($z-$axis) between galaxies; s_1, rotation spin for galaxy 1; s_2, rotation spin for galaxy 2. Rotation spins can only take values of -1 or 1, for clockwise and counterclockwise rotation respectively. Due to the fact that spins have different characteristics with respect to the other parameters they need to be handled different by the mutation genetic operator. There is no restriction in the range of values for each parameter, except for the spins and for the masses that can only take positive values.

In the vector sp the parameters are: σ_1 to σ_3, standard deviations for the first three parameters in vector op; P_1 and P_2 are the probability of change of the rotation spin in galaxy 1 and 2 respectively.

For each individual in the initial generation, the simulator program is executed, with the set of object parameters as inputs to the program. At the end of the simulation, an image and its mass distribution are returned and evaluated according with the fitness function (section 3.3).

After the p simulations are finished and their fitnesses calculated, a new population is created based on genetic operators. 10% of the new population is created by cross-over; average operator creates 10% and 80% is created by mutation.

Cross-over is uniform: two individuals are randomly selected from the original population and each parameter in the two individuals has the same probability to be selected to form two new individuals.

In the average operator, two individuals (op_1 and op_2) are randomly selected from the original population, then a random value between 0 and 1 (M) is created and two new individuals are created as follows :

$$\begin{aligned} op_{prom1} &= op_1 * M + op_2 * (1 - M) \\ sp_{prom1} &= sp_1 * M + sp_2 * (1 - M) \\ op_{prom2} &= op_2 * M + op_1 * (1 - M) \\ sp_{prom2} &= sp_2 * M + sp_1 * (1 - M) \end{aligned}$$

Finally, the mutation operator is performed by multiplying a random number obtained from a normal distribution with zero mean and standard deviation σ (taken from vector sp), selecting individuals randomly from the original population:

$$op_{mut} = op + N_0(sp) = (m_1 + N_0(\sigma_1), m_2 + N_0(\sigma_2), \Delta z + N_0(\sigma_3))$$

Because of the different nature of spins (they are discrete and can take only two values), they need a different mutation operator. Thus, instead of multipling by a random number, spins are mutated by probability: a random number is generated between 0 and 1 from a uniform distribution for each individual, if this number is bigger than the probability assigned to the given individual in the vector sp, then spin is multiplied by -1.

When the new population is created, we have two populations: parents and children. Following the selection process (μ+λ), where μ is the number of parents and λ (in this case they have the same value) the number of children, we merge both populations and sort by fitness. Then the first μ individuals are selected from this merged population to be the new population.

Dynamical mutation is done by means of a multiplication of the strategy parameters (sp) by a factor, which is defined according to the experiment and if the individual is near or far from the solution. When we have many fit individuals, then we can say that the mutation is successful and it is possible to increment the mutation step to reach (or at least be near of) the solution in less generations; for incrementing the mutation step, vector sp is multiplied by a factor of 2.5. In contrast, when we have many unfit individuals, then we can say that the mutation is unsuccessful and it is necessary to reduce the mutation step, maybe because the solution is near; for reducing the mutation step, vector sp is multiplied by a factor of 0.7. These values have been selected experimentally.

The process of calculating fitness and creating a new population is done for a number n of generations or until a fitness threshold is reached. The number of generations varies depending on the complexity of the problem to solve.

3.2 Simulations

In this work simulations are done using the non-self-gravitating technique, based on the restricted three body problem [9,5], i.e. the interparticle forces are neglected and the discs of particles are influenced only by the gravitational forces from the two points of mass that represent the galactic discs [10]. In essence, any kind of simulation can be used, for example N-body simulations surely would produce better results, but they are very expensive in terms of computational resources; the purpose of using non-self gravitating simulations is to reduce the amount of computation. Because of the use of this kind of simulations, the method presented here is restricted to minor violent types of interactions such as bridges, tails and spiral arms; more violent types such as mergers and encounters need more complex simulations.

We have used a coordinate system such that the $x-y$ plane coincides with the plane of the sky, with the $x-$axis horizontal, and the $z-$axis pointing towards the observer. The coordinate system has a range from -30 to 30 units of length.

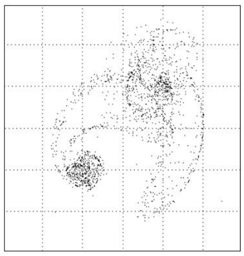
The physical quantities are such that G, the gravitational constant, is equal to 1; the unit of length is taken to be 3 kpc, the unit of time $1 * 10^7$ yr, and the unit of mass $6 * 10^{10} M_\odot$ (solar mass), but other scalings to physical units can be used.

Orbital parameters are not absolutely necessary for running the simulator program. Instead of these, the Cartesian coordinates, masses and velocities are sufficient. Actually, the masses, spins and separation in the line of sight are the parameters shown in the results. Orbital parameters can be determined from these, following the equations given in [5,1]. Parameters used by the simulator program are: masses (m_1 and m_2), three components of the separation vector (Δx, Δy, Δz) and the three components of the velocity (Δv_x, Δv_y, Δv_z). Observations can provide information about velocities along the line of sight (Δv_z) and separations in the plane of the sky (Δx, Δy).

For each simulation a disc of particles is used to represent each galaxy; where particles represent the stars in the galaxy, and each particle can represent more than one star. Distribution of the particles in the disc is done following an exponential distribution, falling with the radius. Following the equations given by the restricted three-body problem, the orbit for each particle is integrated on time using the Runge-Kutta algorithm [7]. At the end of the simulation, an image of the pair of interacting galaxies and its mass distribution are obtained.

3.3 Fitness

At the end of a simulation, the output must be compared with the observational (or synthetic) data to measure the fitness. The method here described requires the data as an image with black pixels, where each pixel represents a portion of the total mass of galaxy. Thus, at the end of each simulation, a grid is superimposed on the image, and the amount of mass in each cell is calculated; Fig. 2 illustrates this process with an image and its grid.



0	0	2	40	31	0
0	2	59	279	152	0
0	39	53	262	184	4
0	157	167	49	88	1
0	148	159	51	44	1
0	1	0	11	0	0

Fig. 2. Artificial image and its grid

The grid has a bi-dimensional size of $L \times L$ cells; in the program the size is 16×16, but other sizes can be used depending on the image size. In order to evaluate a single simulation, the fitness has to be measured. Fitness can be defined in different ways; in this case we define fitness by the following equation:

$$f_m = \sqrt{\sum_{i,j=1}^{L} (m_{i,j} - m_{i,j}^{obs})^2} \tag{1}$$

Where $m_{i,j}$ represents the mass distribution in cell (i,j) obtained from the simulation, $m_{i,j}^{obs}$ is the same quantity obtained from observational (synthetic) data, and the sum extends over the whole grid.

Sometimes the velocity data is also known; in this case such data can be used to measure the fitness of a simulation. Fitness for velocity data is:

$$f_v = \sqrt{\sum_{i,j=1}^{L} (\bar{v}_{i,j} - \bar{v}_{i,j}^{obs})^2} \tag{2}$$

Where $\bar{v}_{i,j}$ and $\bar{v}_{i,j}^{obs}$ denote the average radial velocity in cell (i,j) obtained from the simulation and from observational (synthetic) data respectively. When the two fitness functions are used, the total fitness, with a as a proportionality constant, is:

$$f = f_m + a * f_v \tag{3}$$

4 Results

The results presented here are divided in runs. As mentioned earlier, we have used synthetic data to prove the efficacy of ES. In the beginning of each run, we introduce known parameters to the simulator program and obtain an artificial image with a mass distribution, then we save the image, mass distribution and original parameters and these data are used later to be compared with outputs from ES.

Table 1. Run 1

Generation	m_1	m_2	s_1	s_2	Δz
1	2.0514	1.7060	1	1	3.0143
5	1.5682	0.8425	1	1	3.1538
10	1.6277	0.8684	1	1	4.5527
20	1.3255	0.5374	1	1	3.1007
50	1.2937	0.5303	1	1	1.9049
SD	1.3	0.54	1	1	0

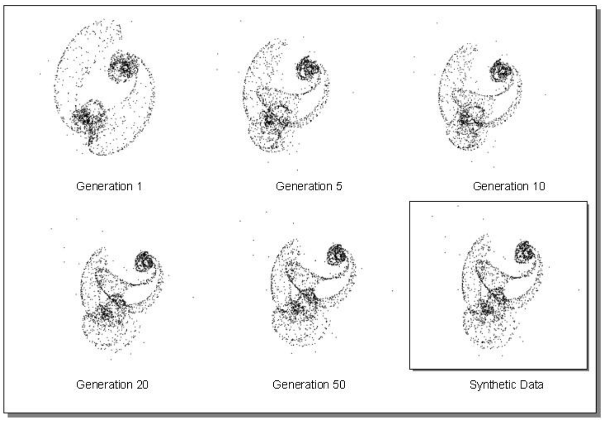


Fig. 3. Image sequence for run 1

The first two runs represent the application of the ES to images with simple geometrical configurations between interacting galaxies. For these two runs, we assume that we only know data about the position of the particles.

As stated before, the parameters shown are: masses, spins and separation in the line of sight. Table 1 and the image sequence in Fig. 3 show the results for run 1. For this run we used 1000 particles per disc, an interaction time of 60 units of time and ran the ES for 100 generations. The first 5 rows show the best simulation in generations 1, 5, 20 and 50; the last row shows the synthetic data (SD). It is clear that the method can estimate the parameters very accurately. Within a few generations the method has found the tendency of the parameters, and at the last generation the parameters are found with great precision. Spins are the first parameters found by ES, this is because an inverse spin would produce a very different morphological configuration at the end of the simulation. Masses are also estimated accurately because the masses are decisive in the morphological structure of the interaction.

Table 2. Run 2

Generation	m_1	m_2	s_1	s_2	Δz
1	1.6473	1.7029	1	1	3.3862
5	1.3993	1.3092	1	1	10.2076
10	0.9120	0.9192	1	1	1.8145
20	1.0261	1.0717	1	1	1.7101
50	1.0013	0.9982	1	1	1.5262
SD	1	1	1	1	0

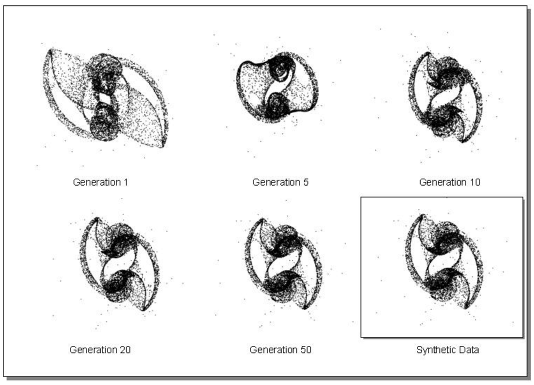


Fig. 4. Image sequence for run 2

Table 3. Run 3

Generation	m_1	m_2	s_1	s_2	Δz	i_1	i_2
5	1.2611	1.1476	-1	-1	2.2990	60.2641	38.3962
10	0.6713	0.8309	-1	-1	7.4265	61.7701	52.1806
20	1.3836	1.2978	-1	-1	6.9343	67.2219	72.9081
50	1.0456	1.0584	-1	-1	5.2163	60.1958	59.0520
100	1.0001	1.0122	-1	-1	5.1476	60.1619	59.4460
SD	1	1	-1	-1	5	60	60

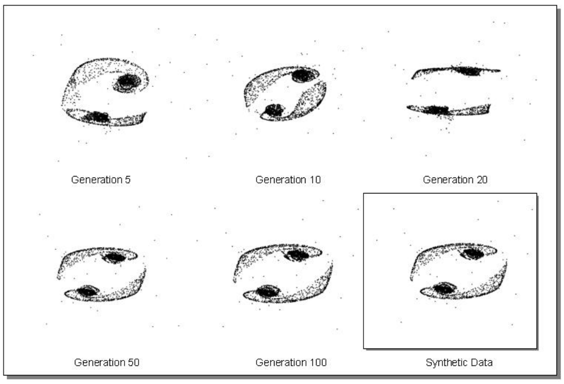


Fig. 5. Image sequence for run 3

Table 4. Run 4

Generation	m_1	m_2	s_1	s_2	Δz	i_1	i_2
5	1.3141	0.0826	-1	1	2.7183	61.0038	18.0867
10	0.9715	0.1067	1	1	1.1835	67.7050	18.1197
20	1.0633	0.0883	1	1	1.4950	61.0191	38.2426
50	1.1027	0.0958	1	1	1.8222	8.3242	30.2229
100	1.0720	0.0872	1	1	2.5981	4.1040	31.1463
SD	1	0.1	1	1	3	0	30

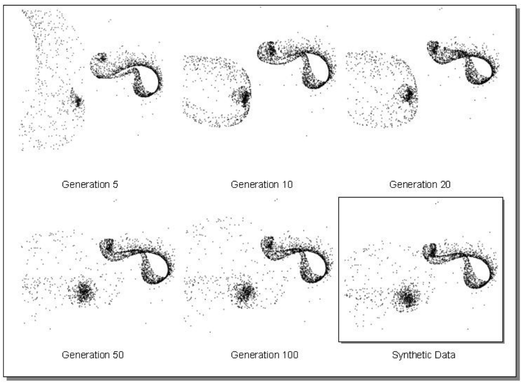


Fig. 6. Image sequence for run 4

Table 2 and the image sequence in Fig. 4 show numerical and graphical results for run 2. In this case all the parameters are equal to unity, the number of particles is 5000 per galaxy and we took the same interaction time and number of generations. As in the previous run, the method finds the parameters with great precision.

In the two previous runs, the separation in the line of sight cannot be found as accurately as the other parameters, the reason is that position data are often not enough to differentiate between images. Thus, in the following two runs the velocity data will be considered. Velocity data helps to differentiate between images where position data are very similar, even when the galactic discs are tilted and the total of particles cannot be distinguished, as in the case of the following runs.

Tables 3 and 4 and image sequences 3 and 4, in Fig 5 and 6 respectively, show the results for runs 3 and 4 of the program. In these cases, additional parameters i_1 and i_2 are shown. These parameters represent the tilt of the galactic discs 1 and 2 respectively. For these runs we used 2000 particles per disc and an integration time of 60 units of time. Because of the inclusion of two additional parameters, the population in ES was evolved over 200 generations.

In these cases, the galactic structure is more complex because the discs are tilted and in run 4 the difference in masses are of one order of magnitude. But even on those circumstances it is clear from the images and the tables that the method can find the parameters very accurately.

5 Conclusions and Future Work

In this work we have applied ES to find the orbital parameters of a pair interacting galaxies, a very important problem in Astrophysics research because it involves many important issues, such as galactic morphological formation and clustering of galaxies. With our solution we are opening the possibility to study a large number of galactic systems due to the automation of this part in the process.

Even with several simplifications done in the test cases used here, searching with ES has demonstrated to be an excellent method for optimization problems where an exploration of continuous parameters spaces is needed. In all the cases the parameters were found with very good precision and ES performed the work with efficiency. Spins and masses were the easiest parameters to find; this is because those parameters are strongly related with galactic morphology. Also, the inclusion of velocity data was important to determinate separation in the line of sight and to differentiate between images with similar position data. Even in the case of tilted discs, ES were able to find the parameters with only a small increment in the number of generations.

5.1 Future Work

In order to improve the method, the possibility of implement a parallelization of the ES could be considered to reduce the necessary time to compute the simulations. Also, simulations based on self-gravitating N-body techniques, incorporating gas dynamics and dark matter, can be employed to see the behavior of ES in more complex situations and to work with real images.

References

1. Boulet, D.: Methods of orbit determination for the micro computer. William-Bell Inc. (1991)
2. Barnes, J. E.: Dynamics of interacting galaxies. `http://ned.ipac.caltech.edu/level5/Barnes/frames.html` (1992)
3. Charbonneau, P.: Genetic algorithms in Astronomy and Astrophysics. ApJS. **101** (1995) 309
4. Dawson, J., Kern, K. and Leung, J.: Genetic algorithms and evolution strategies. `http://www.cpsc.ucalgary.ca/~dawsonj/533/webnotes/main.html` (2000)
5. M. Fitzpatrick, P.: Principles of Celestial Mechanics. Academic Press. (1970)
6. Mitchell, T. M.: Machine learning. McGraw-Hill. (1997)
7. Press, W. H., Teukolsky, S. A., Vetterling, W. T. and Flannery, B. P.: Numerical recipes in C. Cambridge University Press. (1997)
8. Rechenberg, I.: Evolutionsstrategie: optimierung technischer systeme nach prinzipien der biologischen evolution. Stuttgart: Fromman-Holzboog. (1973)
9. Sinclair, C.: Circular restricted three body problem. (1999)
10. Toomre, A. and Toomre J.: Galactic bridges and tails. ApJ. **178** (1972) 623
11. Wahde, M.: Determination of orbital parameters of interacting galaxies using a genetic algorithm. A&AS. **132** (1998) 417