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PAPER

Potentials and limits to basin stability estimation

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Stability assessment methods for dynamical systems have recently been complemented by basin stability and derived measures, i.e. probabilistic statements whether systems remain in a basin of attraction given a distribution of perturbations. Their application requires numerical estimation via Monte Carlo sampling and integration of differential equations. Here, we analyse the applicability of basin stability to systems with basin geometries that are challenging for this numerical method, having fractal basin boundaries and riddled or intermingled basins of attraction. We find that numerical basin stability estimation is still meaningful for fractal boundaries but reaches its limits for riddled basins with holes.

1. Introduction

Going back to the path-breaking ideas of Aleksandr M Lyapunov, dynamical systems are said to be stable if small variations of the initial conditions lead to small reactions of a system, i.e. small perturbations cannot substantially alter the system's time-asymptotic behaviour. This is commonly a statement about the asymptotic behaviour, allowing for large transient deviations if only the system eventually returns to the initial configuration. *Multistable* systems with several attractors add another subtlety to the problem: perturbations may lead to switching from one attractor to another, substantially altering asymptotic behaviour [37]. While infinitesimal perturbations on an attractor have local effects well-studied in the theory of asymptotic stability, finite (including large) perturbations can be critical by causing non-local effects like the transition to another attractor.

A direct method for assessing stability against large perturbations are Lyapunov functions [14, 27, 28], which decrease along trajectories and have local minima on attractors. There are recent approaches to determine them numerically e.g. from radial basis functions [7] or sum of squares decomposition (see e.g. [6] for a comparison of different methods). From an analytic perspective, the method of nonequilibrium potentials [9, 10] determines a special case of Lyapunov functions, namely potentials. This has the additional benefit of yielding transition probabilities between attractors, which is not possible for Lyapunov functions in general. It has further been shown, that nonequilibrium potentials can be constructed for systems with fractal basin boundaries [8, 15]. However, direct methods have in common that Lyapunov functions are typically difficult to find, especially in high dimensions. Furthermore, they return lower bounds on an attractor's basin of attraction, hence it is not possible in general to determine whether a basin shrinks or grows with a parameter change.

Here, we put to test a recent alternative approach to consider non-local perturbations termed *basin stability* S_B . The central idea [31, 32] is to use a kind of volume of the basin of attraction to quantify the stability of attractors in multistable systems subject to a given distribution of perturbations. An advantage of basin stability is that it can be efficiently estimated even in high-dimensional systems and has an intuitive interpretation as a probability to return to an attractor, but it relies on the correct identification of the asymptotic behaviour for a Monte Carlo sample of initial conditions. Basin stability and derived concepts have been successfully applied

recently [39], e.g. for power grids [19, 31, 40, 41], chimera states [29], explosive synchronisation [48] delayed dynamics [25] and resilience measures [34].

The idea of estimating a basin of attraction's area already appears in earlier work, e.g. on the erosion of basin boundaries under parameter variation [38, 43] termed global integrity measure G_τ . It is defined as the fraction from a regular grid of initial conditions that *don't approach* a neighbourhood of an attractor within a given time τ [43]. Hence, the estimate of $S_B(\hat{S}_B)$ and G_τ are linked by $G_\infty = 1 - \hat{S}_B$ and our following discussion on numerical estimation uncertainty also applies to the use case of basin integrity studies.

In numerical simulations, it can be difficult to correctly identify the asymptotic behaviour and determine the attractors. The basin of attraction can practically be defined as the set of all initial conditions whose trajectories enter and stay in some trapping region [35]. Problems may arise if transients are long and chaotic or trajectories stay close to basin boundaries for long, so that numerical errors can move the simulated trajectory across a boundary into a wrong basin and make the simulation converge to a wrong attractor. Principally, three aspects contribute to the overall estimation error: the standard error due to sampling initial conditions, approximation errors in function evaluations or integration of differential equations, and rounding errors due to limited precision. While sampling and approximation errors are controlled by increasing the sample size and the order of approximating polynomials as well as by decreasing step size, rounding errors are typically hard to reduce, which becomes a problem if they are of the same order of magnitude as the other error types. Stochastic systems are additionally subject to the contribution of noise, with intricate effects on the evaluation of trajectories, especially in fractal phase space geometries [22, 44].

Our study thus focuses on the critical case of systems where rounding errors cannot be neglected and may even dominate the overall error due to an intricate state space geometry highly sensitive to numerical imprecision. We put basin stability estimation here to the test by applying it to systems with fractal basin boundaries and riddled or intermingled basins of attraction.

2. Methods

2.1. Basin stability

Consider a system of ordinary differential equations

$$\dot{x} = F(x, t) \quad (1)$$

that has more than one attractor in its state space X . Here, we define an *attractor* as a minimal compact invariant set $A \subseteq X$ whose basin of attraction has positive Lebesgue measure [33]. The basin of attraction of A is the set $B(A) \subseteq X$ of all states from which the system converges to A . Note that in this definition by Milnor, we do not require A to possess an attracting neighbourhood, i.e. to be asymptotically stable. In this sense, also unstable attractors [46] that are separated from their basins of attraction fall into this definition.

Assume the system moves on an attractor A , yet at $t = 0$ a random and not necessarily small perturbation pushes the system to a state $x(0)$ outside A . Assume that $x(0)$ is drawn from a probability distribution with measure μ on X that encodes our knowledge about the frequency of relevant perturbations. E.g., μ may be a uniform distribution on some bounded region $R \supset A$. Note that μ is generally not invariant under a change to the coordinate system.

Will the system converge back to A after the perturbation? To address this, the recent concept of *basin stability* [31, 32] computes the probability measure of B ,

$$\begin{aligned} S_B(A) &:= \mu(B(A)) \\ &= \int_R \mathbf{1}_{B(A)} d\mu \in [0, 1], \end{aligned} \quad (2)$$

i.e., the probability that the system will return to A . The indicator function $\mathbf{1}_{B(A)}(x)$ yields 1 if $x \in B(A)$ and 0 otherwise. We use $S_B(A)$ to quantify just *how* stable the attractor A is against non-infinitesimal perturbations.

The estimation of volume integrals such as equation (2) in high dimensions is a well-known problem, and we assume this is done by simple Monte Carlo sampling [5, 47]. If for each initial state $x(0)$, one can numerically integrate the system $x(t)$ with sufficient precision to decide to which attractor it converges (or whether it diverges), the S_B estimation procedure is thus:

- (i) Draw a sample of $N > 0$ independent initial states from the distribution μ .
- (ii) For each, numerically integrate the system until it is clear whether and where it converges.
- (iii) Count the number M of times the system has converged to A .
- (iv) Use the estimate $\hat{S}_B = \frac{M}{N}$.

Since this is an N -times repeated Bernoulli experiment with success probability S_B , the absolute standard error of the estimate \hat{S}_B due to sampling is $\sqrt{S_B(A)(1 - S_B(A))/N}$, independently of the system's dimension. Thus, the procedure can be applied to high-dimensional systems without necessarily increasing the sample size N , although it may take longer to assess convergence. This is of course since we are not interested in the basin of attraction's *geometry* but only in its *volume* w.r.t. the measure μ .

Note that when the relative std. err. of \hat{S}_B is more relevant than the absolute std. err., smaller values of $S_B(A)$ require larger sample sizes, of the order $N \sim 1/S_B(A)$, since for small $S_B(A)$, the rel. std. err. is $\sim 1/\sqrt{NS_B(A)}$. The divergence of the sample size for very small probabilities to be estimated (i.e. rare attractors with a small basin of attraction and $S_B(A) \ll 1$) is a common problem where (simple) Monte Carlo methods are likely to fail [5]. However, even if $S_B(A)$ is not small, the geometries of the multiple basins of attraction may still make the estimation of S_B difficult for another reason: for some initial conditions $x(0)$ it may be quite difficult to decide where $x(t)$ converges to, since the trajectory may start or come quite close to the boundary between the different basins. Consequently, approximation and rounding errors (rather than sampling errors) in the integration may become relevant and may make the simulated trajectory hop across a basin border, leading to a wrong assessment of where $x(t)$ actually converges to.

2.2. Challenging types of basins

Particularly, a correct convergence assessment becomes difficult if the basins have *fractal* boundaries, influencing the predictability of a system's behaviour in the long run [13, 30, 35]. Imagine we randomly draw initial states from a box through which the boundary between the basins of two attractors runs. Suppose each initial state is specified up to a certain numerical error ε . Then for an initial state that is closer to the boundary than ε , it is uncertain to which of the two attractors the system will converge. Denote by $f(\varepsilon)$ the fraction of initial states for which the outcome is uncertain subject to an initial error ε , i.e. the *uncertainty fraction* [11, 30]. If the boundary is a smooth curve, then these states are all located inside a strip of width 2ε along this curve, and $f(\varepsilon)$ is just proportional to ε . However, if the boundary is fractal, then $f(\varepsilon) \propto \varepsilon^\alpha$. If $\alpha < 1$, the system exhibits *final state sensitivity*, i.e., to decrease the uncertainty one needs a substantial improvement in the knowledge of initial conditions. In a way, this power law scaling leads to an *obstruction of predictability* [11] very similar to the sensitive dependence on initial conditions in chaotic systems.

Predicting the long-term behaviour—the essence of estimating $S_B(A)$ —of systems with fractal basin boundaries may be hard [30] although generally, for most initial conditions, the final state sensitivity is much smaller than the unpredictability of the actual trajectory.

Another extreme case are attractors whose basins are not open as for most systems [33] but rather have an empty interior. The complement of such a *riddled basin* intersects every disk in a set of positive measure [1, 21, 23, 36]. This means that *all* points in its basin of attraction have pieces of *another* attractor basin arbitrarily closely nearby [36]. Physical systems exhibiting riddled basins are the damped, periodically-driven particle moving in a special potential landscape [45] or coupled time-delayed systems [2, 4, 16]. There are also experimental observations for laser-cooled ions in a Paul trap [42] indicating a riddled phase space structure. It has been shown that riddled basins of attraction can also be induced by the addition of noise to the dynamics [22]. For an extensive discussion on riddled/intermingled basins of attraction and fractal basin boundaries, a review appeared in [24].

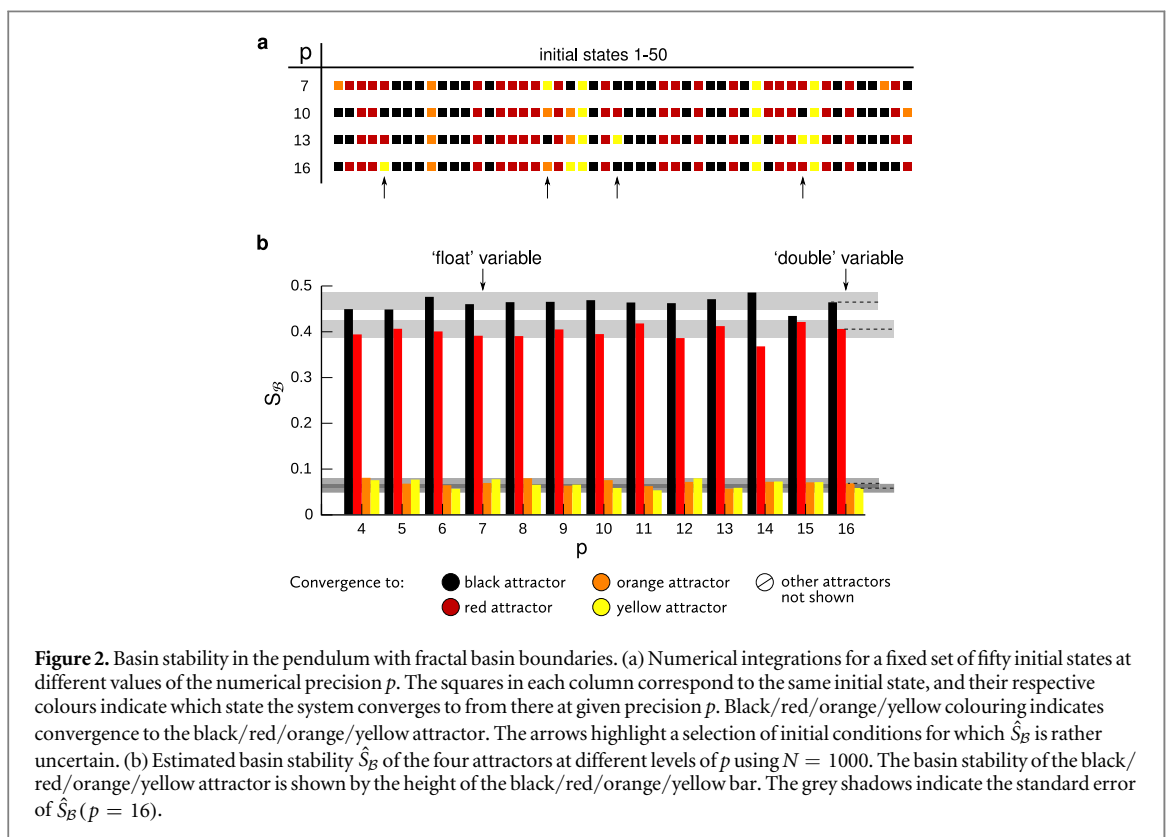
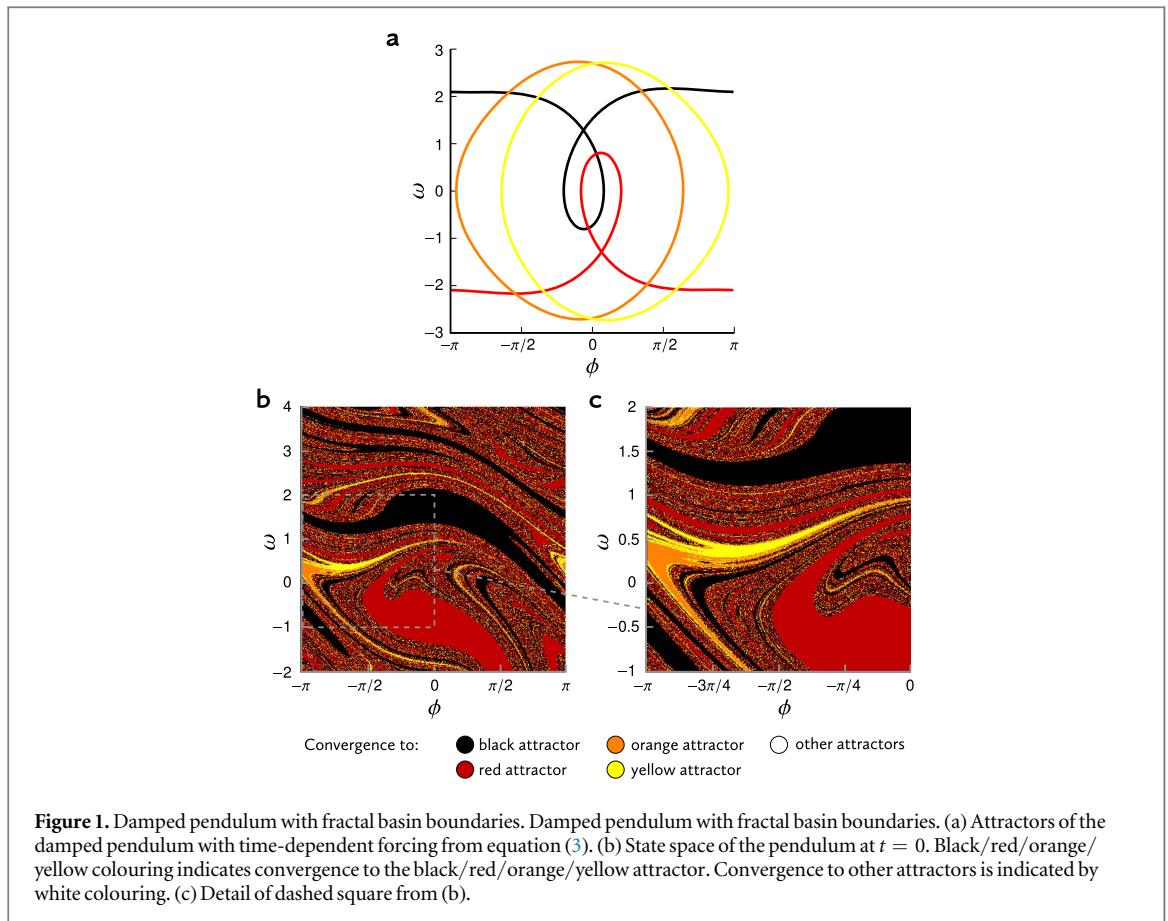
To investigate the behaviour of the estimation procedure, we study two quite different exemplary systems, the continuous-time Wada pendulum with fractal basin boundaries and the discrete-time quadratic map on the complex plane with riddled/intermingled basins of attraction.

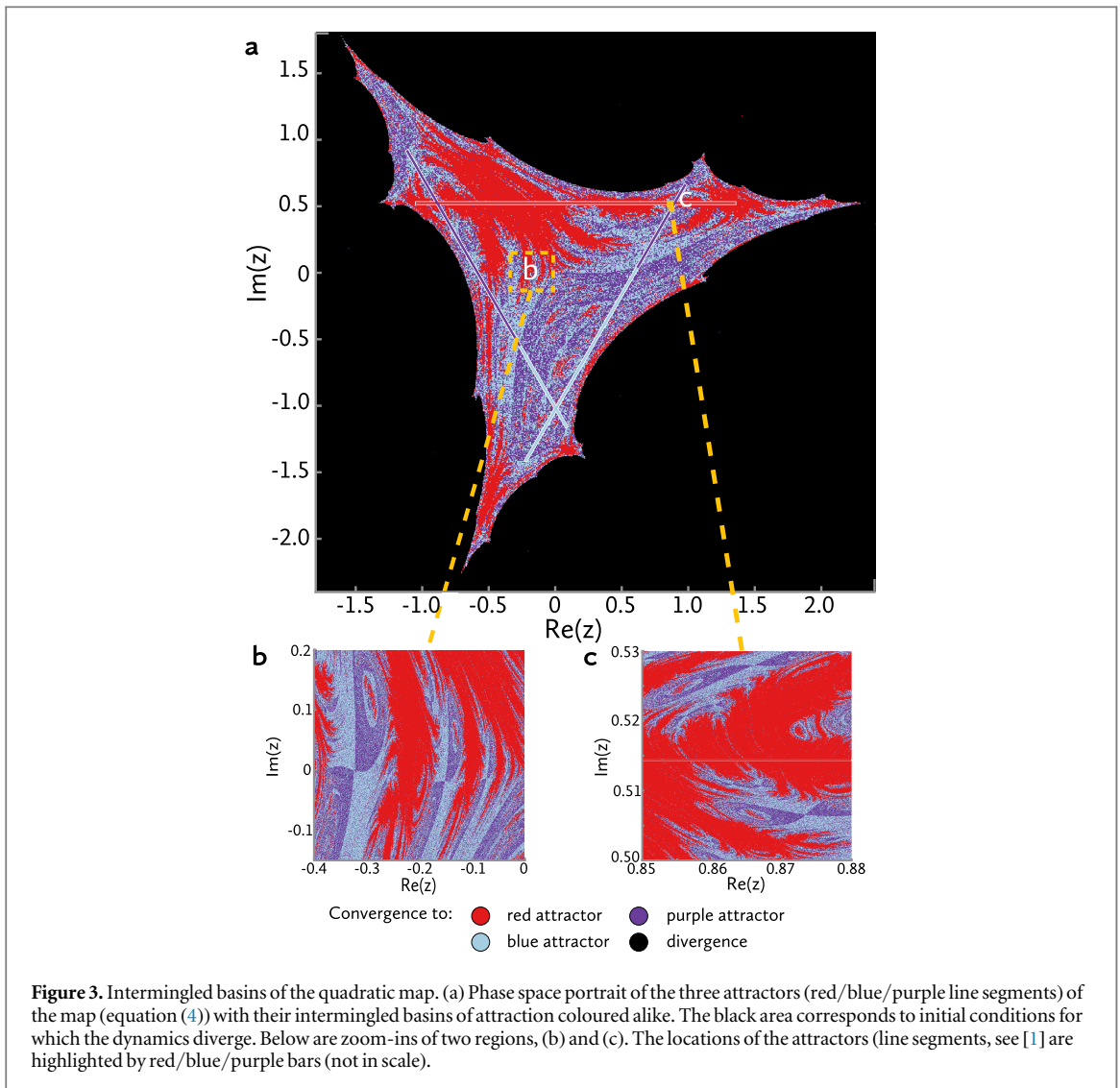
3. Results

Let us first investigate how fractal basin boundaries impact the accuracy of \hat{S}_B by studying the *Wada pendulum* [3, 12]. Consider a damped, driven pendulum that is subject to a time-dependent forcing:

$$\begin{aligned}\dot{\phi} &= \omega, \\ \dot{\omega} &= X \cos t - \alpha\omega - K \sin \phi.\end{aligned}\tag{3}$$

For $\alpha = 0.1$, $K = 1$ and $X = 7/4$, this system has several attractors [18]. The four dominant of them, all limit cycles with period 2π , are shown in figure 1(a): the black and red attractors correspond to rotations of the pendulum, and the orange and yellow attractors are librations. Their respective basins of attraction at $t = 0$ are shown in figure 1(b). Certain regions in this figure appear sprinkled with dots belonging to the different basins, i.e. the boundary between the basins is not easily discernible and remains so when zooming in (figure 1(c)). It is a fractal, resulting in this case from the so-called Wada property of the basins.





Three (or more) subsets of a space are said to have the *Wada property* if any point on the boundary of one subset is also on the boundary of the two others [18, 35]. For the pendulum, the black basin, the red basin and the union of the orange and yellow basins have the Wada property [18, 35]. This means that starting within the rounding error ε of the boundary, a trajectory could in principle converge to *any of the four* attractors.

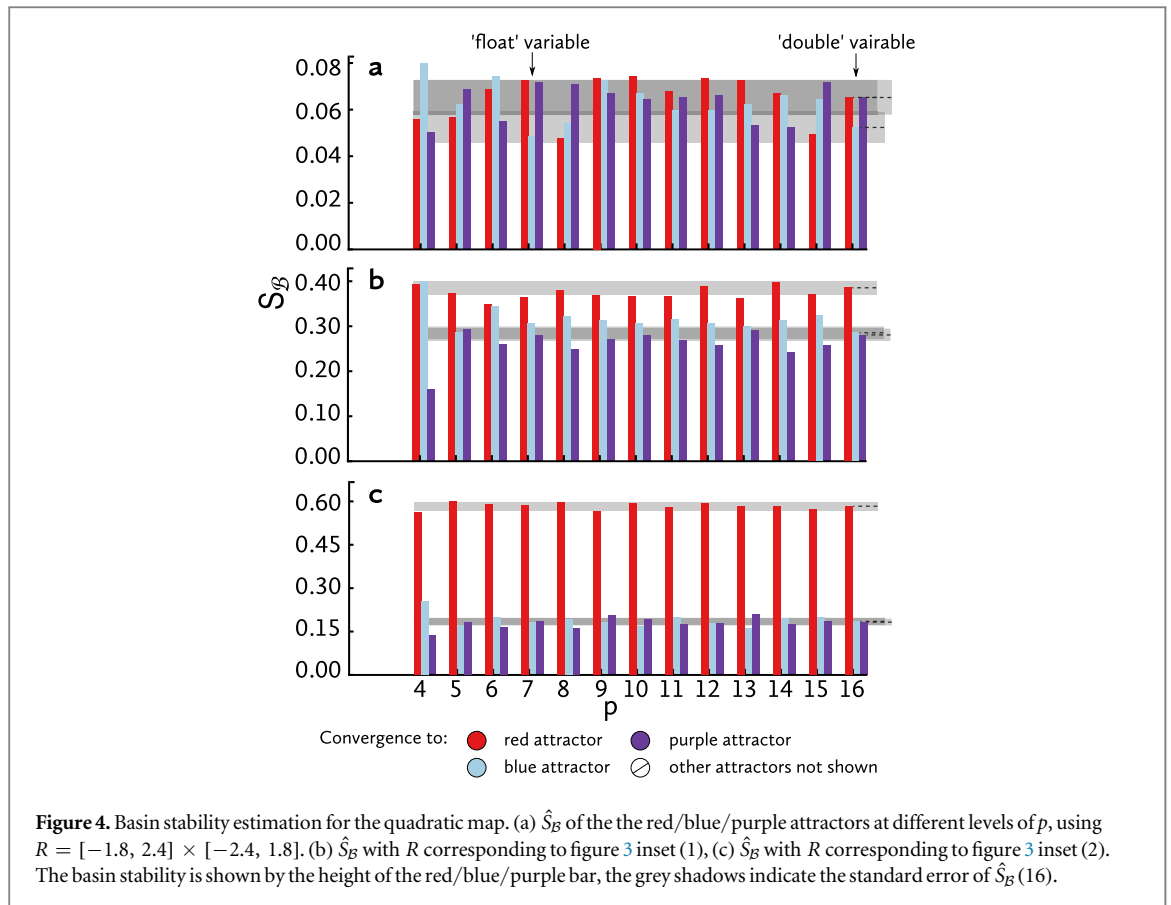
To verify this empirically, we write $\varepsilon = 10^{-p}$ with p denoting *precision*, and discard all information after the p th significant decimal digit in the floating point variables used in all individual operations of the numerical integration. We use 64 bit double precision to allow for a maximum of $p = 16$, while using untruncated 32 bit single precision would correspond to $p \approx 7$. For different values of p , we integrate a fixed set of 50 initial states $x(0)$, drawn uniformly at random from the rectangle $R = [-\pi, \pi] \times [-2, 4]$. The integration stops when a trajectory is close to an attractor within the given precision.

Figure 2(a), reveals that some initial states, particularly those indicated by arrows, indeed lead to different outcomes for different values of p . To investigate how \hat{S}_B depends on p , we let μ be the uniform distribution on R yielding a sample of $N = 1000$ random initial states which are integrated with different precision p , leading to estimates $\hat{S}_B(p)$. As depicted in figure 2(b), there seems to be no systematic influence of p on $\hat{S}_B(p)$. Indeed, most of the individual values of $\hat{S}_B(p)$ are within one standard error of the most precise value $\hat{S}_B(16)$. This suggests that, in contrast to long-term prediction for *individual* initial states (see figure 2(a)), \hat{S}_B is robust under variation of p .

In the following, we investigate the impact of riddled basins of attraction on \hat{S}_B using a conceptual example [1, 26], i.e. the following quadratic map on the complex plane:

$$F_\lambda(z) = z^2 - (1 + \lambda i)\bar{z}. \quad (4)$$

Following the treatment in [1], we study the map for $\lambda = 1.02871376822$. This map has three different attractors on the complex plane which are shown in figure 3; for simplicity they are referred to as the red/blue/



purple attractors with their respective basin of attraction in the following. Interestingly, the three basins of attraction are not just riddled, they are *intermingled*. A basin of attraction is called intermingled if *any* open set which intersects one basin in a set of positive measure also intersects *each* of the other basins in a set of positive measure [17, 20].

The fact that there is a positive probability to end up in a different attractor around each initial condition inside a riddled/intermingled basin of attraction renders these systems effectively non-deterministic [45]. As in the case of Wada boundaries, slight variations of initial conditions or numerical imprecision will affect any forecast of the system's long-term behaviour.

Again, we investigate the effect of limited numerical precision on the significance of \hat{S}_B . In figure 4(a) we depict the result of estimating S_B for varying p using $R = [-1.8, 2.4] \times [-2.4, 1.8]$, i.e. the region pictured in figure 3(a). We observe a large variation of \hat{S}_B of up to 50% compared to the most precise estimation $\hat{S}_B(16)$ and no systematic dependence on p .

In figure 3(c) we zoomed into the neighbourhood of the red attractor, where the share of the corresponding red basin is increasing in proximity of the attractor. In particular, the measure of this basin of attraction, restricted to an ϵ -neighbourhood of the attractor, approaches unit probability for $\epsilon \rightarrow 0$ [1]. This apparent behaviour provides an explanation for figure 4(c) where we determined $\hat{S}_B(p)$ for figure 3(c). In contrast to our previous observation, the fluctuations of $\hat{S}_B(p)$ almost stay within one standard error and the estimation appears to be more robust. For reference, figure 4(b) depicts $\hat{S}_B(p)$ for figure 3(b) not containing any (part of) an attractor. On the one hand, the variation of $\hat{S}_B(p)$ exceeds one standard error, up to about 20% compared to $\hat{S}_B(16)$, such that our estimation is more sensitive to numerical imprecision than in figure 4(b); on the other hand the variations are smaller than in our first experiment.

4. Discussion

We applied the Monte Carlo estimation procedure of basin stability in two cases, basins with fractal boundaries and riddled/intermingled basins of attraction. In the fractal boundaries case, we find that while the asymptotic properties of individual trajectories still cannot be determined robustly, the converse is true for the basin stability estimation. It remains an open question for future research, how exactly (in a quantitative sense) the numerical estimation uncertainty might be derived from the actual basin geometry. In the riddled/intermingled case,

however, we find that the results can vary drastically with the chosen precision. The effect of rounding errors is comparable or even larger than the standard error of the sampling. Only if the sample region R is chosen in some sense ‘close enough’ to the actual attractor of interest, the foliated structure of the surrounding basins allows for a meaningful numerical estimation.

While we here study the effect of small numerical errors on the asymptotics in deterministic systems, a somewhat complementary work [44] considers the effect of noise on transient properties, i.e. the escape probability from a constrained region. As this example shows, it is an interesting aspect for further research to combine these approaches and study the additional effect of noise on final state determination.

In our two prototypical examples, the phase space dimension is low, i.e. two and three, while basin stability estimation is especially advantageous in high-dimensional systems compared to complementary methods (e.g. Lyapunov functions). Given that the phase space dimension does not affect the standard error of the estimation process, we have no reason to assume a different behaviour between low and high dimensions. Conversely, we expect that estimation problems inherent to our examples and strategies to cope with them equally apply to high-dimensional systems and are important to be considered in future research.

5. Conclusion

What are practical implications for the application of basin stability? In general, it is sufficient if the rounding error of an estimation is smaller than its sampling error to get a significant result. However, any numerical procedure is subject to a finite numerical precision and we have to assume that in practice it will not be high enough to reach this goal in dynamical systems with intricate basin geometries. If there is no prior knowledge available, a good starting point is to actually visualise the interesting part of the phase space to get a first idea of the appearance of, e.g., fractal sets. If any are detected, it is necessary to use the highest available numerical precision p_h to get $\hat{S}_B(p_h)$, potentially avoiding artefacts respectively insignificant estimations. We suggest to repeat the S_B estimation at a lower numerical precision p_l and take the difference $\hat{e}_p = |\hat{S}_B(p_h) - \hat{S}_B(p_l)|$ as a straight-forward (rough) estimator of the variability of $\hat{S}_B(p)$ with p and, by way of extrapolation, as a rough estimate of the remaining standard error of $\hat{S}_B(p_h)$ as an estimate of S_B due to finite numerical precision. To assess the influence of rounding errors on \hat{S}_B then compare \hat{e}_p with the standard error of $\hat{S}_B(p_h)$ as an estimate of $S_B(p_h)$ due to sampling, which can be estimated as $\hat{s}_p = \sqrt{\hat{S}_B(p_h)(1 - \hat{S}_B(p_h))/N}$. If $\hat{e}_p < \hat{s}_p$, rounding has no significant effect on the estimation quality. For instance, this could be implemented by comparing the results at double and single precision computations.

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References

- [1] Alexander J, Yorke J A, You Z and Kan I 1992 Riddled basins *Int. J. Bifurcation Chaos* **02** 795–813
- [2] Ashwin P and Timme M 2005 Unstable attractors: existence and robustness in networks of oscillators with delayed pulse coupling *Nonlinearity* **18** 29
- [3] Battelino P M, Grebogi C, Ott E, Yorke J A and Yorke E D 1988 Multiple coexisting attractors, basin boundaries and basic sets *Physica D* **32** 296–305
- [4] Chaudhuri U and Prasad A 2014 Complicated basins and the phenomenon of amplitude death in coupled hidden attractors *Phys. Lett. A* **378** 713–8
- [5] Evans M and Swartz T 2000 *Approximating Integrals via Monte Carlo and Deterministic Methods (Oxford Statistical Science Series)* 20 (Oxford: Oxford University Press)
- [6] Gajduk A, Todorovski M and Kocarev L 2014 Stability of power grids: an overview *Eur. Phys. J.: Spec. Top.* **223** 2387–409
- [7] Giesl P, Hamzi B, Rasmussen M and Webster K N 2016 Approximation of Lyapunov functions from noisy data arXiv:1601.01568
- [8] Graham R, Hamm A and Tél T 1991 Nonequilibrium potentials for dynamical systems with fractal attractors or repellers *Phys. Rev. Lett.* **66** 3089–92
- [9] Graham R and Tél T 1984 Existence of a potential for dissipative dynamical systems *Phys. Rev. Lett.* **52** 9–12
- [10] Graham R and Tél T 1986 Nonequilibrium potential for coexisting attractors *Phys. Rev. A* **33** 1322–37
- [11] Grebogi C, McDonald S W, Ott E and Yorke J A 1983 Final state sensitivity: an obstruction to predictability *Phys. Lett.* **99A** 415–8
- [12] Grebogi C, Nusse H E, Ott E and Yorke J A 1988 Basic sets: sets that determine the dimension of basin boundaries *Lecture Notes in Mathematics* **1342** 220–50
- [13] Grebogi C, Ott E and Yorke J A 1983 Fractal basin boundaries, long-lived chaotic transients, and unstable-unstable pair bifurcation *Phys. Rev. Lett.* **50** 935–8
- [14] Hahn W 1958 Über die Anwendung der methode von Ljapunov auf differenzgleichungen *Math. Ann.* **136** 430–41
- [15] Hamm A, Tél T and Graham R 1994 Noise-induced attractor explosions near tangent bifurcations *Phys. Lett. A* **185** 313–20
- [16] Jiang Y 2000 Globally coupled maps with time delay interactions *Phys. Lett. A* **267** 342–9
- [17] Kan I 1994 Open sets of diffeomorphisms having two attractors, each with an everywhere dense basin *Bull. Am. Math. Soc.* **31** 68–74

- [18] Kennedy J and Yorke J A 1991 Basins of Wada *Physica D* **51** 213–25
- [19] Kim H, Lee S H and Holme P 2016 Building blocks of the basin stability of power grids *Phys. Rev. E* **93** 062318
- [20] Lai Y C and Grebogi C 1995 Intermingled basins and two-state on-off intermittency *Phys. Rev. E* **52**
- [21] Lai Y-C and Grebogi C 1996 Characterizing riddled fractal sets *Phys. Rev. E* **53** 1371–4
- [22] Lai Y- C and Grebogi C 1996 Noise-Induced riddling in chaotic systems *Phys. Rev. Lett.* **77** 5047–50
- [23] Lai Y-C, Grebogi C, Yorke J and Venkataramani S 1996 Riddling bifurcation in chaotic dynamical systems *Phys. Rev. Lett.* **77** 55–8
- [24] Lai Y-C and Tél T 2011 Transient chaos *Applied Mathematical Sciences* vol 173 (New York: Springer)
- [25] Leng S, Lin W and Kurths J 2016 Basin stability in delayed dynamics *Sci. Rep.* **6** 21449
- [26] Lopes A O 1992 On the dynamics of real polynomials on the plane *Comput. Graph.* **16** 15–23
- [27] Lyapunov A M 1907 Problème Général de la Stabilité du Mouvement *Ann. Fac. Sci. Toulouse: Math.* **2** 203–474
- [28] Malisoff M and Mazenc F 2009 Constructions of strict Lyapunov functions *Communications and Control Engineering* 1st edn (London: Springer)
- [29] Martens E A, Panaggio M J and Abrams D M 2016 Basins of attraction for chimera states *New J. Phys.* **18** 022002
- [30] McDonald S W, Grebogi C, Ott E and Yorke J A 1985 Fractal basin boundaries *Physica D* **17** 125–53
- [31] Menck P J, Heitzig J, Kurths J and Hans-Joachim S 2014 How dead ends undermine power grid stability *Nat. Commun.* **5** 3969
- [32] Menck P J, Heitzig J, Marwan N and Kurths J 2013 How basin stability complements the linear-stability paradigm *Nat. Phys.* **9** 89–92
- [33] Milnor J 1985 On the concept of attractor *Commun. Math. Phys.* **99** 177–95
- [34] Mitra C, Kurths J and Donner R V 2015 An integrative quantifier of multistability in complex systems based on ecological resilience *Sci. Rep.* **5** 16196
- [35] Nusse H E and Yorke J A 1996 Wada basin boundaries and basin cells *Physica D* **90** 242–61
- [36] Ott E, Alexander J, Kan I, Sommerer J and Yorke J 1994 The transition to chaotic attractors with riddled basins *Physica D* **76** 384–410
- [37] Pisarchik A N and Feudel U 2014 Control of multistability *Phys. Rep.* **540** 167–218
- [38] Rega G and Lenci S 2005 Identifying, evaluating, and controlling dynamical integrity measures in non-linear mechanical oscillators *Nonlinear Anal.: Theory Methods Appl.* **63** 902–14
- [39] Rodrigues F A, Peron T K D, Ji P and Kurths J 2016 The Kuramoto model in complex networks *Phys. Rep.* **610** 1–98
- [40] Schäfer B, Matthiae M, Timme M and Witthaut D 2015 Decentral smart grid control *New J. Phys.* **17** 15002
- [41] Schmietendorf K, Peinke J, Friedrich R and Kamps O 2014 Self-organized synchronization and voltage stability in networks of synchronous machines *Eur. Phys. J.: Spec. Top.* **223** 2577–92
- [42] Shen J-L, Yin H-W, Dai J-H and Zhang H-J 2008 Riddled basin of laser cooled-ions in a Paul trap *Chin. Phys. Lett.* **13** 81–4
- [43] Soliman M S and Thompson J M T 1989 Integrity smooth measures and quantifying basins the erosion of of attraction *J. Sound Vib.* **135** 453–75
- [44] Soliman M S and Thompson J M T 1990 Stochastic penetration of smooth and fractal basin boundaries under noise excitation *Dyn. Stab. Syst.* **5** 281–98
- [45] Sommerer J C and Ott E 1993 A physical system with qualitatively uncertain dynamics *Nature* **365** 138–40
- [46] Timme M, Wolf F and Geisel T 2002 Prevalence of unstable attractors in networks of pulse-coupled oscillators *Phys. Rev. Lett.* **89** 154105
- [47] von Neumann J 1951 Various techniques used in connection with random digits *Monte Carlo Method: National Bureau of Standards Applied Mathematics Series* **12** 36–8
- [48] Zou Y, Pereira T, Small M, Liu Z and Kurths J 2014 Basin of attraction determines hysteresis in explosive synchronization *Phys. Rev. Lett.* **112** 114102