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Use of Modal Analysis and Surrogate Solution Surfaces to Analyze and Assess Adaptive Autonomous Systems

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NOTICES

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14. ABSTRACT

A method is proposed by which to analyze the logic of adaptive autonomous system (AS) models through diverse scenarios by treating them as "black-box" models and developing solution surfaces of these models by incrementing their input parameters over the whole parameter range. The different modes of the AS are expected to be recognizable on the solution surface. Gradient analysis can be used to identify the transition regions between modal zones. The use of surrogate solution surface calculations is proposed to ease the computational burden of the black-box analysis. The proposed method is expected to remain viable when the model input parameters are greater than two and visualization of the solution surfaces becomes difficult. Recalculating the solution surface in time as the AS model is put though a mission and analyzing changes in modal transition regions will indicate the adaptation, or learning, of the AS model as it performs its mission.

15. SUBJECT TERMS

autonomous systems analysis, surrogate surface generation, high-dimension solution surfaces, gradient analysis, black-box analysis

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Contents

List of Figures

1. Introduction

Autonomous systems (ASs) are characterized by decision-making abilities performed in real time. ASs can range from simple automated systems such as modern washing machines that can adjust the water levels required to wash a load of laundry to deep space probes that are designed to perform a mission with complete autonomy. Most autonomous systems of interest are of intermediate complexity—systems that can interpret sensor data of their environment and make decisions that will allow them to carry out their mission. Some ASs have (or will have) the capability to retain data of past decisions and their consequences, and adapt their future decision making to effectively "learn" during their missions.

ASs can have a wide range of functionality and applications, from those examples already cited to driverless vehicles, unsupervised data-network-intrusion detection, adaptive radar and communication systems, and just about any system whose human supervision can be replaced with digital or mechanical logic.

Because of the exceptional range and variety of ASs, a general method is sought to analyze and assess large categories of ASs as opposed to developing methods to analyze the capabilities and reactions of individual ASs.

The sensor and actuator subcomponents of an AS can be individually specified in the AS design and therefore are not considered in this general performance analysis. Because of the decision-making capability of an AS, it is expected to change modes of operations as it performs its mission. For example, an automated drone is expected to take evasive action to avoid collision if it senses an obstruction in its flight path. Moreover, these mode changes will change over time as adaptive ASs learn from their environment. This analysis is thus focused on the time-dependent intermodal behavior of the AS.

2. Development of Numerical Solutions to AS Models

ASs are expected to be designed using numerical models, and these models can be used to analyze and assess the AS design. Because of the complexity, decision-making nonlinearity, and high scenario variability expected in the AS models, as well as the need to keep the generality of the analysis method high, the AS models are considered as "black boxes", exercised with different values of input parameters and analyzed by the comparison of model output.

Mission scenarios and environments found around the AS can vary greatly, and because of that the AS model should be fully exercised by varying the model's input parameters individually over their whole range of possible values. Thus, fully exercising a model having a single input parameter (1D) produces a solution displayed as a curve (Fig. 1). Fully exercising a model with two input parameters (2D) produces a solution surface (Fig. 2). Models with higher dimensions lead to solution matrices that are hard to visualize but remain nonetheless analyzable.

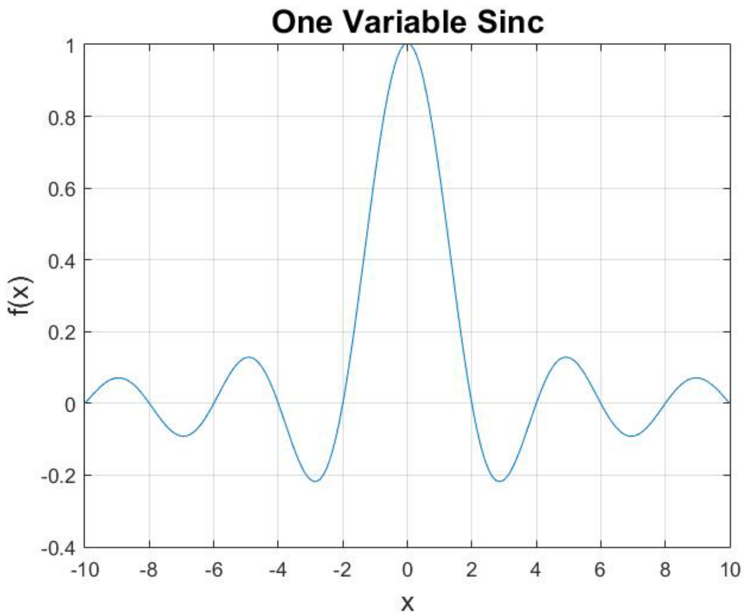

Fig. 1 Normalized solution curve of a one-parameter sinc model

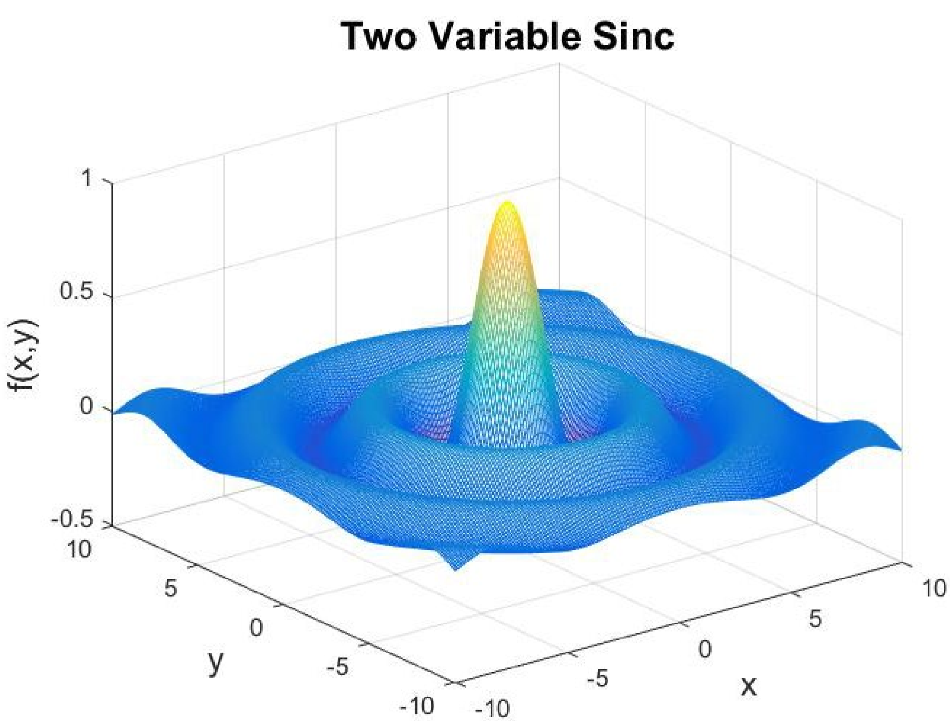

Fig. 2 Normalized solution surface of a two-parameter sinc model

3. AS Modal Zone Hypothesis

The decision-making abilities of an AS imply that it will behave differently, or behave in different modes, in response to specific input parameter values. It is hypothesized that these operational modes manifest themselves as recognizable zones on the model solution surfaces. To illustrate, different zones have been established on the two-parameter sinc function solution shown in Fig. 2 and presented in Fig. 3. The zones are defined by Eqs. 1–3.

$$z_1(x,y) = 0.5 \quad \begin{cases} x < -5 \\ y > 5 \end{cases}. \tag{1}$$

$$z_2(x,y) = 1 \quad \begin{cases} x > 5 \\ y > 5 \end{cases}. \tag{2}$$

$$z_3(x,y) = -0.5 \quad \begin{cases} x > 5 \\ y < -5 \end{cases}. \tag{3}$$

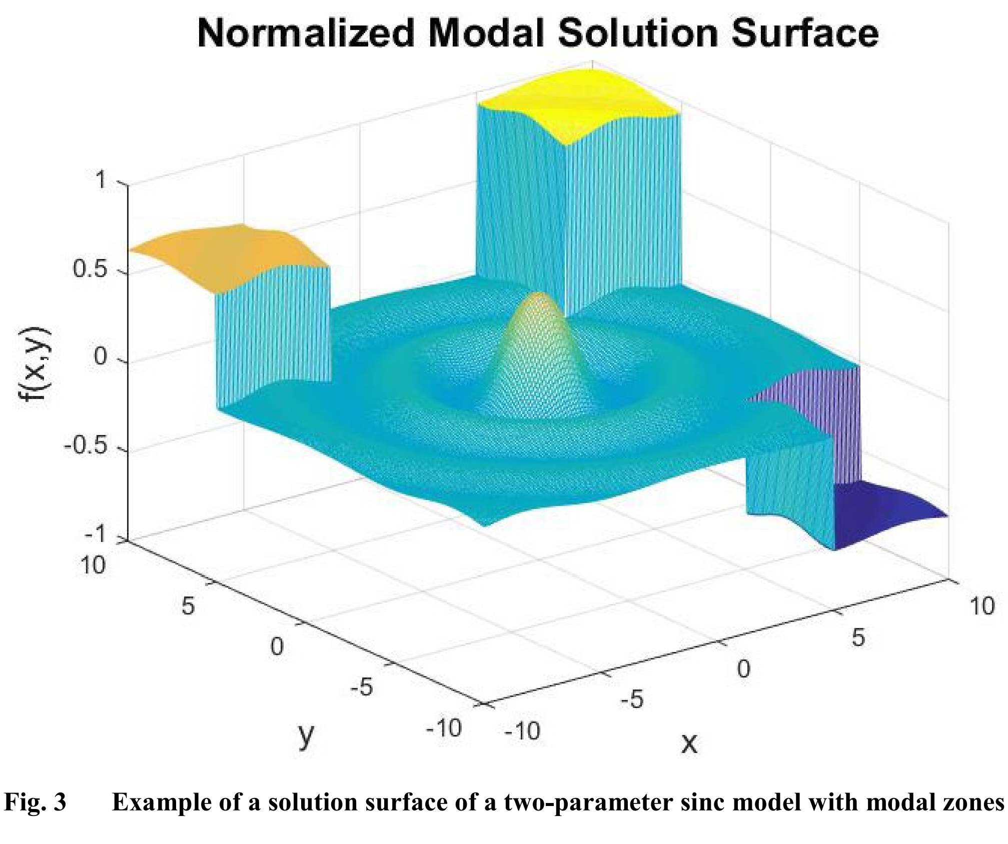

Fig. 3 Example of a solution surface of a two-parameter sinc model with modal zones

An extension of the hypothesis is that since the modal zones manifest themselves on the model's solution surface, there will be a definable transition region as the model solution goes from one mode to another. It is these transition regions that are indicative of modal changes in the black-box AS model solution, and the analysis of the location of the transition regions indicate whether the model is behaving as expected.[1]

A good way to numerically determine the transition regions locations on the solution surface is by calculating the solution surface gradients. Figure 4 shows the gradient with respect to each input variable, superimposed on a single plot.

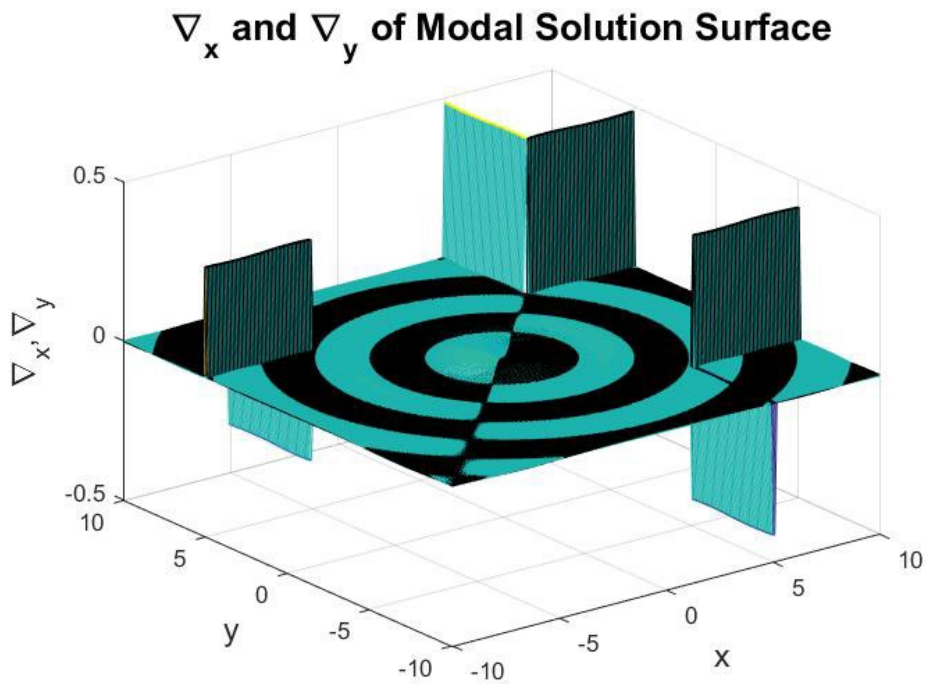

Fig. 4 Gradients of the modal solution surface clearly showing the transition region locations

Although the modal transitions are easy to visualize in the simple, two-parameter model solution surface presented in Fig. 2, they may not be as obvious in higher-dimension models that cannot easily be visualized. The analysis of models whose input parameters may not be completely independent from each other may obfuscate the location of the transition zones.

4. Analysis of Adaptive, or "Learning" AS Models

The adaptation of the AS to changing environment, changing mission, or changing self-status poses additional challenges to the analysis of these models. Near-real-time adaptation, or learning, changes the mode transition regions of the model solution surfaces in time, and therefore requires multiple calculations of the solution surfaces as the AS model is exercised through a scenario to analyze whether the AS model is learning as expected. Figure 5 shows a hypothetical learning progression as two of the three modal zones change size in time.

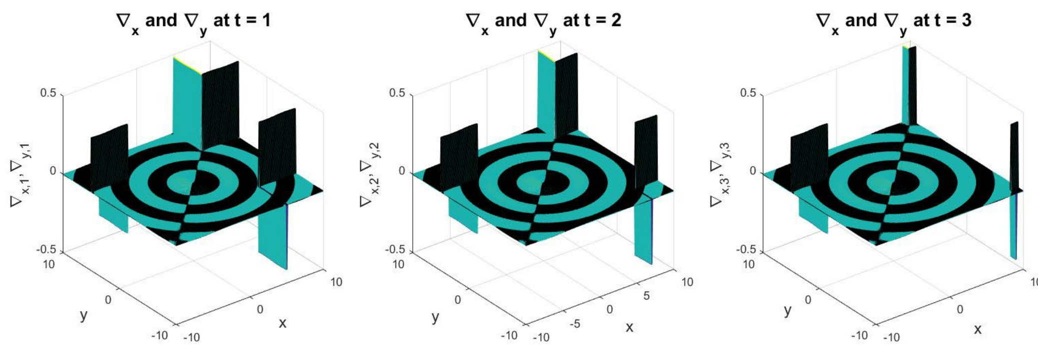

Fig. 5 Time series of modal solution surface gradient showing changes in mode transition region sizes. This indicates the AS is learning.

5. Surrogate Solution Surfaces vs. Full Calculation of the AS Model

The procedure described to analyze the model of an adaptive AS model requires the calculation of multiple solution surfaces from the model. The example used, namely that of a two-variable sinc function, is very inexpensive to calculate. In reality, AS models evaluated as black-box systems are expected to be more complicated and expensive to exercise over the full range of input parameters. The brute force approach of calculating the model by incrementing each input variable in turn quickly becomes unobtainable when the model has more than a few input parameters.

The surrogate model construction method[2] uses unequal parameter increments to optimize the construction of the surrogate solution surface with as few calculations as possible. The surrogate model construction is a global optimization method that is used specifically for computation of expensive black-box problems. By using the surrogate model construction, the modal sinc function solution, shown in Fig. 6, was reconstructed with 1099 calculations and a median mean square error (MSE) of less than 0.0001. The original modal sinc function displayed in Fig. 3 used 40,401 model calculations to generate. The three mode regions, albeit distorted, are still observable in the surrogate solution surface. A debate is possible on whether 40,401 points were necessary to capture the modal regions of the original modal sinc function solution in Fig. 3, but it is emphasized that the surrogate solution surface checks whether the MSE of the constructed solutions surface is at or below the specified level, and continues refining the solution until it is. The surrogate solution method is thus expected to be more efficient than the brute force method.

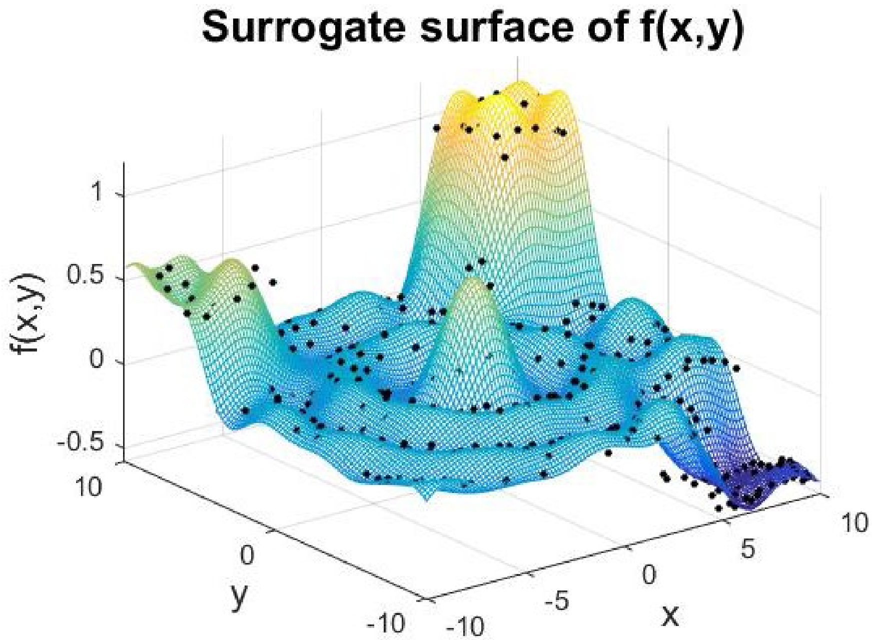

Fig. 6 Surrogate solution surface calculation of the modal sinc function and the points where the model was calculated

The input variable gradients of the surrogate surface can be calculated and are shown in Figs. 7 and 8. Both clearly show the transition zones of the modal sinc function surrogate reconstruction, whose location can be analyzed for proper model performance.

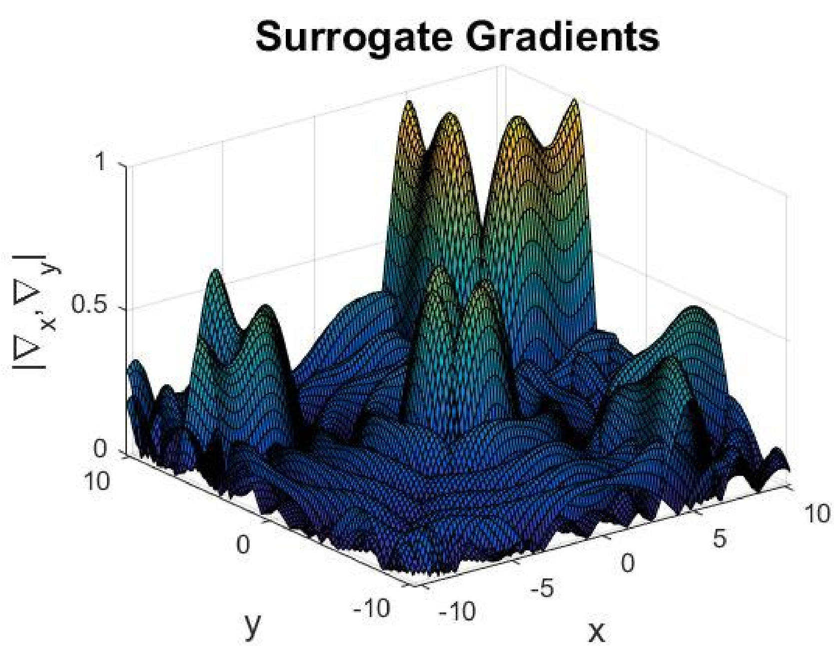

Fig. 7 Gradient amplitude of the surrogate solution surface of the two-input parameter sinc function

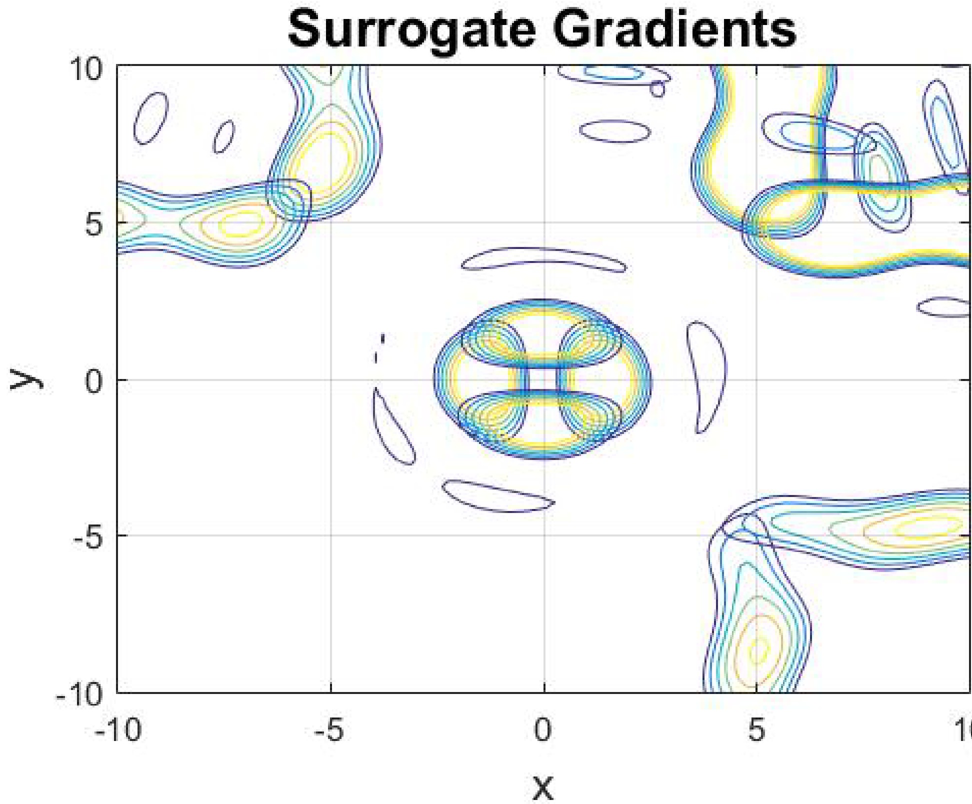

Fig. 8 Contour plot of the gradient amplitudes of the surrogate solution surface of the sinc function

As before, a time series of the surrogate gradients can be calculated to analyze the behavior of the adaptive AS model exposed to mission adaptation or environmental changes. A time sequence of the surrogate solution surface gradient is shown in Fig. 9. As in Fig. 4, two of the three modal regions are modeled smaller with time. The gradients of the calculated surrogate solution surface that define the mode transitions are clearly visible.

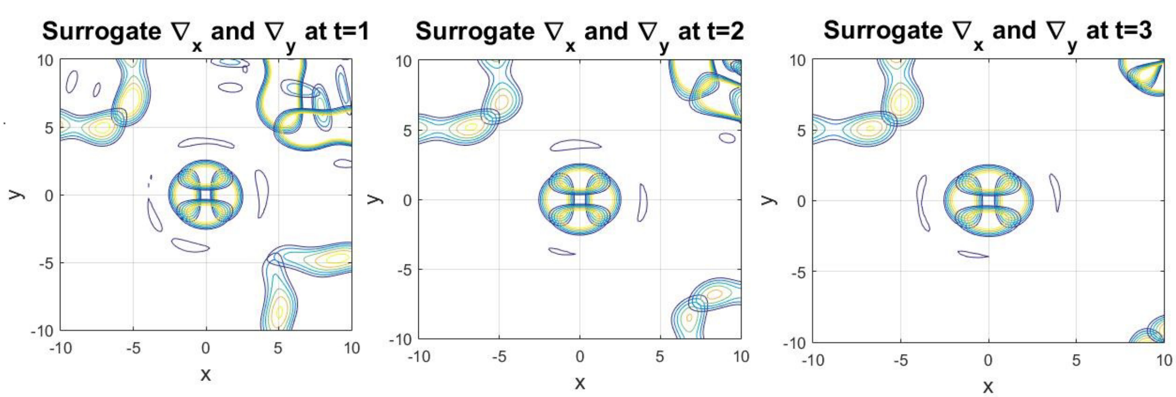

Fig. 9 Time sequence of the model surrogate solution surface showing changing modal zones. This sequence shows a method to analyze an adaptive AS.

Control of Surrogate Surface Approximation

Detection of subtle function detail, to include smaller or irregular-shaped modal zones, can be obtained through internal control of the surrogate solution surface program. More detail of the surrogate surface solutions makes this calculation more expensive. Figures 10 and 11 show the surrogate solution surface of the 2D sinc functions with a complicated modal zone. The modal zone defined by the following boundaries,

$$z_1 = 1 \quad \begin{cases} -9 < x < -2 \\ \;\; 9 > y > \;\; 2 \end{cases}, \tag{4}$$

is superimposed by a smaller modal zone with boundaries defined by

$$z_2 = 2 \quad \begin{cases} -7 < x < -4 \\ \;\; 7 > y > \;\; 4 \end{cases}. \tag{5}$$

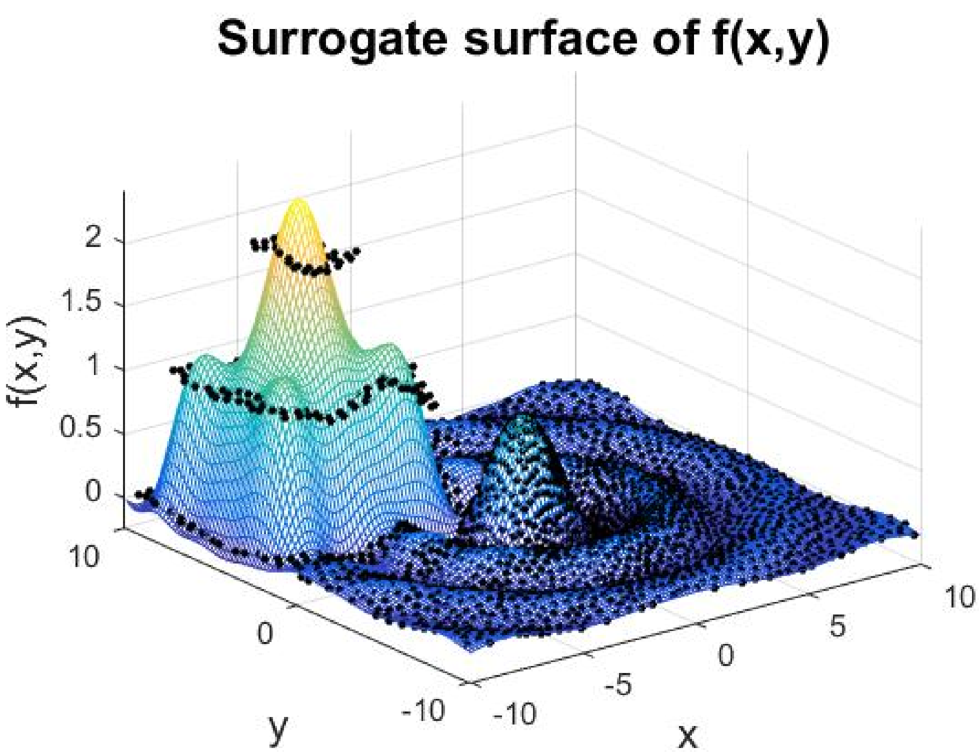

Fig. 10 Surrogate surface of a 2D sinc function with a complicated modal zone and the points where the model was calculated

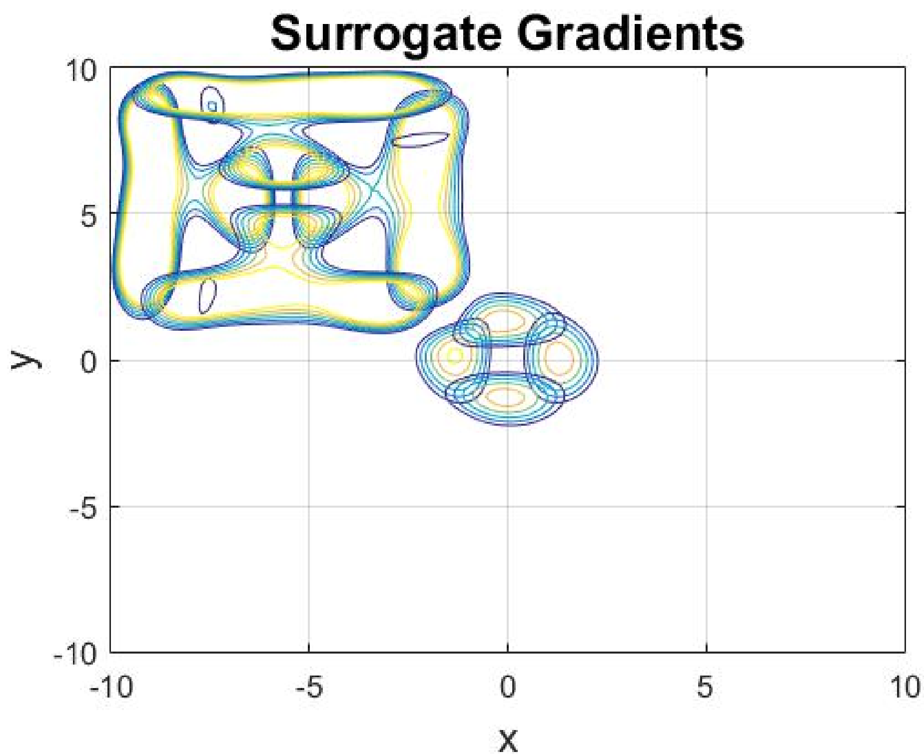

Fig. 11 Contour plot of the gradient amplitudes of the surrogate solution surface of the sinc function with a complicated modal zone

The transition region of the second modal zone is clearly visible in Fig. 11. The surrogate surface was calculated with 3609 points.

6. Conclusions

A general method to fully analyze the modal behavior of adaptive autonomous systems has been described, and demonstrated on an inexpensive, 2D variable sinc function. To minimize the amount of model calculations needed for the analysis, the surrogate global optimization method is employed.

A 2D model was used to allow visualization of the analysis capability of this method and to keep the iterative and surrogate calculations inexpensive. This analysis method is readily extendable to more-realistic, higher-dimensional AS models that have more input variables, and whose solution surfaces are harder to visualize. The surrogate solution method will become more important when exercising a more expensive, higher-dimensional model as a black-box model.

A previously unreported novelty described in this report is the ability to analyze adaptive AS systems by calculating several solution surfaces as the adaptive AS model is run through a scenario where it is expected to learn, and to analyze the changes in modal zones with time that reflect the adaptation of the model to scenario stresses.

This analysis method postulates that the solution surfaces change is amplitude enough to exhibit high-gradient transition regions between modes. This assumption may become more tenuous for higher-dimensional models where interdependency of input variables exist. Yet because gradients are calculated for each variable, the transition regions for each variable should still be recognizable if they have a large transition gradient.

7. References

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