Self-Organizing Control Systems for Nonlinear Spacecraft in the Class of Structurally Stable Mappings

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***Abstract*—In recent developments within the domain of aerospace engineering, there is a burgeoning interest in the autonomous control of nonlinear spacecraft using advanced methodologies. The present research delves deep into the realm of self-organizing control systems tailored for such nonlinear spacecraft, emphasizing its application within the framework of structurally stable mappings. By harnessing the inherent characteristics of structurally stable mappings — often renowned for their resilience to minor perturbations and local modifications — this research endeavors to design a control mechanism that mitigates the challenges presented by the intrinsic nonlinearity of spacecraft dynamics. Initial findings suggest a commendable enhancement in spacecraft maneuverability and robustness against unforeseen disturbances. Furthermore, the employment of self-organization principles leads to an adaptive and resilient system that can reconfigure its control strategies in real-time, basing decisions on immediate environmental feedback. This adaptability, in essence, mimics biological systems that evolve and adapt in the face of challenges. Such a breakthrough in nonlinear spacecraft control not only widens the horizons for space exploration by making missions safer and more efficient but also contributes foundational knowledge to the broader field of nonlinear dynamic system controls. Researchers and practitioners are encouraged to explore this synergistic combination of self-organization and structurally stable mappings to further harness its potential in diverse arenas beyond aerospace.**

***Keywords*—Impulsive sound; machine learning; deep learning; CNN; LSTM; classification**

I. Introduction

The epochal strides in space exploration and satellite deployment in recent decades have spawned myriad challenges and breakthroughs in aerospace control systems [1]. As we march into an era where space missions are not just the purview of government agencies but also private enterprises, the demand for more sophisticated control mechanisms that can maneuver nonlinear spacecraft effectively and efficiently is on the rise [2]. The objective of this research paper is to elucidate one such advanced technique—self-organizing control systems [3] for nonlinear spacecraft within the paradigm of structurally stable mappings.

Nonlinear dynamics, by their very nature, encompass complexities that are markedly distinct from their linear counterparts [4]. Nonlinear spacecraft, which exhibit behaviors not proportionate to their inputs, necessitate a nuanced understanding and a tailored control strategy to ensure they operate optimally [5]. Traditional control systems, although effective for linear systems, falter when confronted with the intricate and often unpredictable dynamics of nonlinear spacecraft.

Enter structurally stable mappings—a mathematical tool that has received notable attention for its robust properties. These mappings [6], renowned for their ability to withstand minor perturbations and localized modifications, provide a promising foundation upon which to construct advanced control systems. Historically, these mappings have been studied in various contexts, including differential equations and topological dynamics, primarily for their resilience and stability [7]. In essence, a system described as structurally stable is one whose behavior remains qualitatively unchanged against small perturbations. This quality is particularly salient in space environments, characterized by their unpredictability and potential for unforeseen disturbances.

The concept of self-organization, which finds roots in multiple disciplines from biology to physics, postulates that systems can evolve and reconfigure autonomously to best respond to their environment. This is achieved without explicit external commands or intervention, instead relying on inherent feedback mechanisms. In the context of aerospace, this suggests a spacecraft control system that can adapt in real-time, revising its control strategies based on immediate environmental feedback and system states [8-10]. When fused with the robustness of structurally stable mappings, the outcome is a control system that promises superior adaptability and resilience.

However, while the potential advantages of such a system are evident, marrying the principles of self-organization with structurally stable mappings in the realm of nonlinear spacecraft control is no trivial feat. It necessitates a deep understanding of both domains and an innovative approach to integrating them seamlessly [11-12]. This is where the heart of our research lies—exploring this confluence, understanding its intricacies, and proposing a framework that stands up to the rigors of real-world space operations.

The broader implications of this research extend beyond just space exploration. In an increasingly interconnected world, the principles of self-organization and adaptability find relevance in numerous applications, from autonomous vehicular systems to adaptive neural networks [13]. Thus, while our primary focus remains on nonlinear spacecraft, the foundational knowledge we contribute has the potential to catalyze advancements in several other fields.

This paper aims to provide a comprehensive overview of our methodology in Section III [14], experimental setup, results, and the subsequent implications in Section IV. Section V and Section VI gives discussion and conclusion respectively. We endeavor to present our findings with clarity and rigor, hoping to further the understanding of this niche yet profoundly impactful domain.

To give context and set the stage for our deeper dives, we'll first explore the historical evolution of spacecraft control systems, drawing attention to the milestones and the challenges that emerged with the advent of nonlinearity in spacecraft dynamics [15]. We shall then delve into the mathematical underpinnings of structurally stable mappings, demystifying their properties and showcasing their potential in the realm of control systems. Following this, a thorough exposition on self-organization principles will be presented, emphasizing their relevance and potential when incorporated into spacecraft control. Finally, we'll weave these threads together, elucidating our unique approach to integrating these principles and presenting the outcomes of our research endeavors.

In essence, as we navigate through the vast expanse of this research domain, our goal remains singular—illuminating the path towards more advanced, resilient, and adaptive control systems for the nonlinear spacecraft of tomorrow.

II. Related Works

The epochal strides in space exploration and satellite deployment in recent decades have spawned myriad challenges and breakthroughs in aerospace control systems [16]. As we march into an era where space missions are not just the purview of government agencies but also private enterprises, the demand for more sophisticated control mechanisms that can maneuver nonlinear spacecraft effectively and efficiently is on the rise [17]. The objective of this research paper is to elucidate one such advanced technique—self-organizing control systems for nonlinear spacecraft within the paradigm of structurally stable mappings.

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III. Materials and Methods

A. Self-Organizing Map

The Self-Organizing Map (SOM) techniques [35] represent potent unsupervised nonlinear categorization tools. Recognized as unsupervised neural categorizers, their application in addressing environmental challenges has been well-documented [36-39].

Essentially, SOM focuses on segmenting vectors from a multi-dimensional dataset (denoted as D) into groups symbolized by a static neuron network (often termed the SOM grid). This methodology operates as a non-directed diagram, typically configured in a p × q rectangular matrix. Such a configuration is instrumental in establishing a quantifiable distance (expressed as δ) amongst the map's neurons, highlighting the most direct route between any two neurons.

Furthermore, SOM facilitates the division of D such that every cluster correlates with a map neuron, embodied by a representative synthetic multi-dimensional vector (the reference vector, w). Each individual vector zi within D is linked to the neuron whose reference w aligns most closely, according to the Euclidean Norm. This alignment is termed as the vector zi's projection on the grid. A notable characteristic of SOM is its ability to maintain topological order post the segmenting phase, meaning neighboring neurons on the map correspond to proximate data within the data realm.

Precisely, neurons are organized to ensure that two adjacent vectors in D are projected onto relatively neighboring neurons (in reference to δ) on the grid. Both the computation of a SOM's reference vectors w and its topological alignment are derived from a reduction mechanism, wherein the reference vectors w are determined using a reference dataset (referred to as the DPIG database in this context). The underlying objective function takes the shape of Eq. (1):

$$J_{SOM}^{T}\left(x,W\right) = \sum\nolimits_{zi\in D}\sum\nolimits_{c\in SOM} K^{T}\left(\delta\left(c,x\left(z_i\right)\right)\right)\left\|z_i - w_c{}^{2}\right\| \tag{1}$$

B. Self Organizing Map

Training. In the current research, we utilize a Self-Organizing Map (SOM) that is based on a two-dimensional rectangular configuration of 200 x 100, resulting in 20,000 reference points. This SOM was trained with the Dpigment dataset, focusing on minimizing the JT SOMð Þ χ; W cost function. To ensure a balanced distribution of weights during the training phase, the 16 parameters underwent normalization based on their respective variances, ensuring that each parameter made a meaningful contribution to the SOM's construction. Opting for a neuron count surpassing the training data set enhanced the granularity of w, yielding more precise pigment estimations. Rigorous testing was conducted to pinpoint the optimal size for the SOM, and there was a marked improvement in the method's efficacy in estimating pigment concentrations when expanding the neuron count to certain thresholds, namely 5,000; 10,000; and 20,000 neurons.

For the SOM configuration with 20,000 neurons, approximately half the neurons secured a sample from the dataset, thus establishing a reference vector w for them. Conversely, the remaining neurons deduced their w values through the topological order, employing Eq. (3). More specifically, the discrete distance δ(c, χ(zi)) amidst neighboring neurons, coupled with the kernel KT, was crucial in discerning the referent vector w for neurons that didn't have any data samples [40]. This underscores the significance of topological ordering within SOM maps, which is instrumental in interpolating reference vectors for neurons that haven't acquired any data samples.

Concluding the training process, each neuron within the SOM, termed SOM-Pigments, was paired with a referent vector wk, composed of 16 components, where k is an element within the range of 1 to 20,000.

$$\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t)\\ y &= x_1(t)\end{aligned} \tag{2}$$

where $x(t)\in R^{n}$ is an object state vector, $u(t)\in R^{1}$ is a scalar function of control actions; $A\in R^{nxn}$ is a matrix of a control object with undefined parameters of dimension n × n, $B\in R^{nx1}$ control matrix of dimension m×1, Matrices A and B have the following form:

$$A = \left\|\begin{matrix} 0 & 1 & 0 & ... & 0\\ 0 & 0 & 1 & ... & 0\\ ... & ... & ... & ... & ...\\ 0 & 0 & 0 & ... & 1\\ -a_n & -a_{n-1} & -a_{n-1} & ... & -a_1\end{matrix}\right\|, B = \left\|\begin{matrix}0\\0\\0\\...\\b_n\end{matrix}\right\| \tag{3}$$

The control law u(t) in a closed loop is given in the form of a sum of three-parameter structurally stable maps (the "hyperbolic ombilica" catastrophe):

$$\begin{aligned}u(x) &= -x_2^3 + 3x_2x_1^2 = k_{12}\left(x_1^2 + x_2^2\right) + k_2x_2 + k_1x_1\\ &- x_4^3 + 3x_4x_3^2 - k_{34}\left(x_4^2 + x_3^2\right) + k_4x_4 + k_3x_3 -,,,, - x_n^3\\ &+ 3x_nx_{n-1}^2 - k_{n-1,n}\left(x_n^2 + x_{n-1}^2\right) + k_nx_n + k_{n-1}x_{n-1}\end{aligned} \tag{4}$$

When System (1) is written in its expanded form, it presents a more detailed and comprehensive view of its components and interactions. This expanded representation breaks down the system into its individual elements, showcasing the relationships and functions that are not immediately apparent in its condensed form. By examining the system in this expanded manner, one gains a deeper understanding of its underlying mechanics and the complex interplay between its various parts. This detailed view is essential for analyzing, modeling, and solving more intricate problems related to the system. Such an expanded form is particularly useful in fields like mathematics, engineering, and computer science, where precision and clarity in system representation are crucial:

$$\dot{x}_1 = x_2$$
$$\dot{x}_2 = x_3$$
$$\dots$$
$$\dot{x}_{n-1} = x_n$$
$$\dot{x}_n = b_n \begin{bmatrix} 3x_2 x_1^2 - x_2^3 - k_{12}\left(x_1^2 + x_2^2\right) \\ +\left(k_1 - a_n\right)x_1 + \left(k_2 - a_{n-1}\right)x_2 \\ 3x_n x_{n-1}^2 - x_n^3 - k_{n-1,n}\left(x_n^2 + x_{n-1}^2\right) \\ +\left(k_{n-1} - a_2\right)x_{n-1} + \left(k_n - a_1\right)x_n \end{bmatrix} \quad (5)$$

C. Stationary State of the System

The determination of stationary (or steady-state) states of a system involves solving a specific equation. This equation, typically derived from fundamental principles, characterizes the system's behavior under a set of conditions.

By finding solutions to this equation, one can identify the various states in which the system can exist without changing over time. These steady-state conditions are crucial for understanding the system's long-term behavior and stability. Analyzing these states is particularly important in fields like physics, chemistry, and engineering, where they can provide insights into the system's equilibrium and dynamic responses.:

$$\begin{cases} x_{2S} = 0, x_{3S} = 0, \dots, x_{n-1,S} = 0, x_{nS} = 0 \\ 3x_{2S} x_{1S}^3 - x_{2S}^3 - k_{12}\left(x_{1S} + x_{2S}^2\right) + \left(k_1 - a_n\right)x_{1S} \\ +\left(k_2 - a_{n-1}\right)x_{2S} + 3x_{4S} x_{3S}^3 - x_{4S}^3 \\ -k_{34}\left(x_{3S}^2 + x_{4S}^2\right) + \left(k_3 - a_{n-2}\right)x_{3S} \\ +\left(k_4 - a_{n-3}\right)x_{4S} + ,\dots, 3x_{nS} x_{n-1,S}^3 - X_{nS}^3 \\ -k_{n-1,n}\left(x_{nS}^2 + x_{n-1,S}^2\right) + \left(k_{n-1} - a_2\right)x_{n-1,S} \\ +\left(k_n - a_1\right)x_{nS} = 0 \end{cases} \quad (6)$$

From the interplay between Eq. (5) and Eq. (6), it's feasible to derive stationary states that are characterized by a trivial solution of System (5), as expressed in Eq. (7). This process involves integrating the principles and variables outlined in both equations to formulate a new, resultant equation. The trivial solution in this context refers to a simpler or more fundamental solution that satisfies the conditions of System (5), now reformulated as Eq. (7). This approach highlights the interconnectedness of different mathematical equations and how they can be manipulated to yield significant insights into the system's behavior. Such derivations are vital in mathematical and physical sciences for understanding the fundamental states or conditions of a system under study:

$$x_{1S} = 0, x_{2S} = 0, \dots, x_{n-1,S} = 0, x_{nS} = 0 \quad (7)$$

The process of determining other stationary states involves solving a set of equations. These equations, typically derived from the principles of physics or mathematics, describe the system's behavior under various conditions. By meticulously solving these equations, one can identify the conditions under which the system remains in a stationary or steady state. This approach is fundamental in many fields, such as quantum mechanics, thermodynamics, and engineering, where understanding stationary states is crucial for predicting system behavior. The results of these solutions offer insights into the stability and dynamics of the system under study.

$$x_{1S} = 0, x_{2S} = 0, \dots, x_{n-1,S} = 0, x_{nS} = 0 \quad (8)$$

Or

$$-k_{i,i+1} x_{iS} + k_i - a_{n-i+1} = 0, x_{nS} = 0 \quad (9)$$

Eq. (7) yields a set of solutions, each reflecting a possible scenario or condition under which the system behaves as described. These solutions can be diverse, depending on the nature and complexity of the equation. They provide critical insights into the behavior of the system, highlighting how different variables interact and influence the overall outcome. Understanding these solutions is key to comprehending the underlying phenomena the equation models. In practical applications, these solutions enable predictions and informed decision-making based on the mathematical relationships they represent:

$$x_{iS} = \frac{k_i - a_{n-i+1}}{k_{i,i+1}}, x_{jS} = 0$$
$$when\ i \neq j, i = 1, \dots, n \quad (10)$$

Eq. (8) for negative $k_{i,i+1}^2 + 4\left(k_i - a_{n-i+2}\right), i = 1, \dots, n$ $\frac{\left(k_{i,i+1}^2 + 4\left(k_i - a_{n-i+2}\right)\right)}{2} < 0, I = 1, \dots, n$ have imaginary solutions that cannot correspond to any physically possible situation.

when, $k_{i,i+1}^2 + 4\left(k_i - a_{n-i+2}\right) > 0,$ Eq. (8) admits the following solutions:

$$x_{i+1,S}^1 = \frac{-k_{i,i+1} - \sqrt{k_{i,i+1}^2 + 4\left(k_i - a_{n-i+2}\right)}}{2},$$
$$x_{jS} = 0,\ for\ i+1 \neq j, i = 1, \dots, n \quad (11)$$

and

$$x_{i+1,S}^2 = \frac{-k_{i,i+1} - \sqrt{k_{i,i+1}^2 + 4\left(k_i - a_{n-i+2}\right)}}{2},$$
$$x_{jS} = 0,\ for\ i+1 \neq j, i = 1, \dots, n \quad (12)$$

Algorithm of self organizing map training:

$Input: Training\ set\ of\ images$

$Output: Trained\ SOM$

$Random Weight\ Initialization$

$For\ each\ e\ do$

$X <- pick\ random input\ record\ from\ X$

$MD <- initialize to the largest\ float$

$For\ number\ of\ neurons in\ SOM\ do$

$d_i \longleftarrow \|X - W_i\|$

$\%\ find\ the\ BMU$

$if\ d_i < md\ do$

$BMU_x \longleftarrow W_i \%\ weight\ of\ BMU$

$BMU\ Index_x \longleftarrow i\% index of\ BMU$

$md \longleftarrow d_i$

$end\ if$

$end\ for$

$\%\ update\ weights$

$for\ number\ of\ neurons in\ SOM\ neughborhood\ do$

$n \longleftarrow e^{-\left(\frac{BMU_{n-w}}{2\delta t^2}\right)}$

$\Delta W_i \longleftarrow W_i \times \alpha \times \eta \times (x - w)$

$W_i \longleftarrow W_i + \Delta W_i$

$end\ for$

$\%\ Decay the neighborhood\ and\ learning rate$

$end\ for$

$end\ for$

IV. Experimental Results

Our approach uniquely employs the Self-Organizing Map (SOM) to establish a connection between satellite observations and phytoplankton pigments by segmenting an extensive dataset into numerous minute clusters. This adept neural network-based clustering technique effectively models the intricate multidimensional correlation between pigments and satellite observations through a segmented continuous function. Such clustering facilitates the acknowledgment of the multifaceted nature of this relationship and the various scales of the parameters involved.

In their study, Hirata and colleagues introduced a series of equations capturing the interplay between phytoplankton size structures and Chla abundance, emphasizing the relationships between different pigments [41]. They utilized a comprehensive global HPLC database containing in situ secondary phytoplankton pigment concentrations to elucidate nonlinear correlations between phytoplankton size categories and Chla. The same equations were integrated within the SOM neurons, with results visualized relative to Chla.

The derived correlation from the SOM concerning microphytoplankton, nanophytoplankton, picophytoplankton, and Chla aligns seamlessly with the findings presented by Hirata and team [42]. Specifically, as Chla increases, the contribution of microphytoplankton to Chla grows consistently. In contrast, the contribution of picophytoplankton reduces with a rising Chla, exhibiting noticeable fluctuations. Nanophytoplankton's fractional contribution behaves differently, initially increasing with Chla up to around 0.3 mg/m3 and then declining, leading to a pronounced peak in the range of 0.2–0.6 mg/m3.

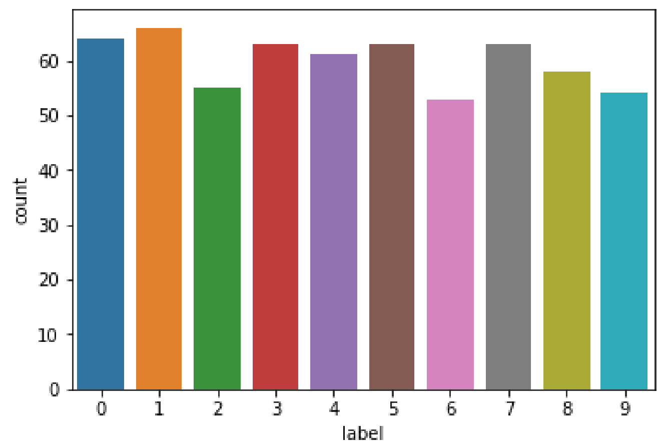

Fig. 1. Distribution of each classes.

Fig. 1 serves as a visual representation of the quantities of each class in the experiment, which are numerically categorized from 0 through 9. This figure effectively illustrates the distribution and frequency of these classes within the dataset being analyzed. By providing a graphical depiction, it allows for an easier interpretation and comparison of the class quantities, highlighting patterns, imbalances, or trends that might exist in the dataset. Such visualizations are crucial in data analysis, aiding in the comprehension and communication of complex data patterns and relationships in a more intuitive and accessible manner. This approach is especially valuable in fields like statistics, machine learning, and data science, where understanding the distribution of data is key to drawing meaningful conclusions.

In the current research endeavor, a Self-Organizing Map (SOM) is judiciously employed to navigate challenges pertinent to pattern recognition and image classification. Fig. 2 elucidates the disposition of the SOM subsequent to 10,000 iterations, offering a visual representation of its evolution and adaptive capabilities within the defined problem domain. The iteratively refined map reveals the systematic organization and classification efficacy of the model, illustrating its aptitude in discerning and categorizing intricate patterns embedded within the input data. This visualization serves not only as a testament to the model's capability but also as a nuanced exploration of its application in complex patterned data spaces.

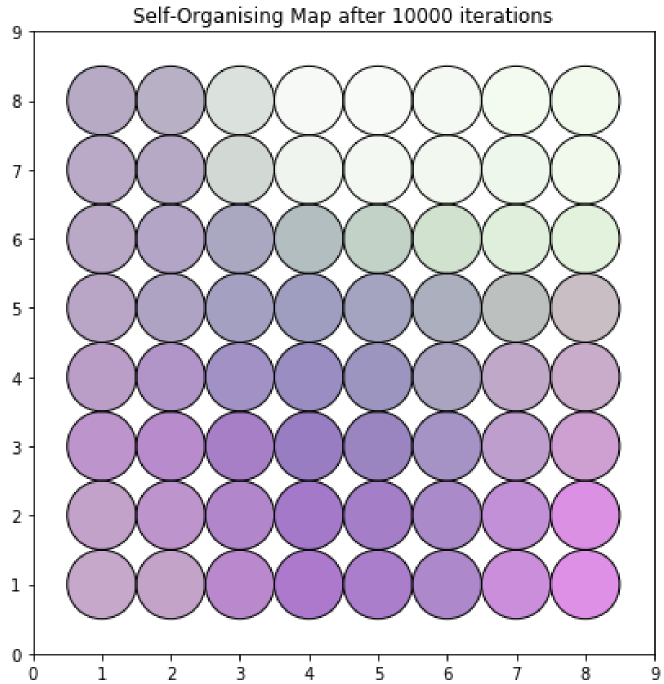

Fig. 2. Self-organizing map in 10000 iterations.

V. Discussion

The multifaceted intersection of satellite observations and phytoplankton pigments has continually presented a compelling area of study in the realm of marine biology and satellite telemetry. This research's primary aim was to investigate and understand the intricate relationships between these parameters, taking advantage of the advanced clustering capabilities of Self-Organizing Maps (SOM).

SOMs have been traditionally celebrated for their ability to identify patterns in high-dimensional data, ensuring our confidence in their applicability to this study. Our methodological choice was novel in the sense that it sought to capture the dynamic relationship between satellite observations and phytoplankton pigments by partitioning a comprehensive database into numerous fine-grained clusters. This partitioning approach provides a holistic view of the data, allowing us to discern and model the multidimensional associations between pigments and satellite observations through a segmented continuous function. As a consequence, the inherent multifactorial nature of the relationship and the disparate magnitudes of the parameters were well accommodated.

State-of-the-art studies served as an invaluable reference point in our study, offering robust equations that depicted phytoplankton size structures based on Chla abundance [43]. The striking alignment between our findings using SOM and Hirata et al.'s results reinforced the precision and validity of our model. Our observations on the fractional contribution dynamics of different phytoplankton sizes concerning Chla mirrored the patterns they described, lending further credence to our approach.

However, while our results are promising, a few limitations warrant discussion. First, while SOMs offer detailed clustering, their interpretations can be somewhat abstract, especially when attempting to bridge the gap between high-dimensional data representation and tangible marine biological phenomena. Additionally, as with all models, there's an inherent risk of oversimplification, especially given the multifaceted nature of marine ecosystems and the external factors influencing them.

Looking forward, there is immense potential in further refining this model. Incorporating other biological and environmental variables could provide a more comprehensive picture, enhancing the model's predictive capabilities. Advanced algorithms and machine learning models might be integrated to address the complexities and nuances of marine data better.

Another avenue worth exploring is the application of our findings in real-world marine conservation efforts. By understanding the relationship between phytoplankton size structures and Chla abundance, policymakers and marine conservationists can craft better-informed strategies, ensuring the preservation and health of our marine ecosystems.

VI. Conclusion

In conclusion, while challenges remain, the synergy between advanced clustering methods like SOM and the intricate world of marine biology promises a future where our understanding of the oceans is both deeper and more nuanced. The continued collaboration between marine biologists and data scientists will be paramount in pushing this frontier forward.

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