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Inherent Behavioral Stochasticity in Soft Robots: Analysis and Control Strategies

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Abstract. The unique composition of soft robots, predominantly constructed from elastomers and polymers, amplifies the likelihood of unpredictability in their performance, setting the stage for significant behavioral stochasticity as compared to their rigid counterparts. In this paper, we present a control-centric perspective on the intrinsic behavioral stochasticity observed in soft robots, exploring the underlying reasons and presenting control methodologies tailored to address the associated challenges. In addition to these challenges, we also provide insights on the potential benefits that the intrinsic behavior of the soft structure can have when they come in contact with unstructural environments. Finally, we discuss the generic control schemes traditionally used with these robots and highlighted potential strategies to alleviate the performance gaps introduced by the inherent unpredictability.

1. Introduction

Literature sees the role of stochasticity central to the adaptation [1] whether it is about responding to the unstructured environment [2, 3, 4], learning by exploring [5, 6], modelling a sophisticated behavior in terms of distributions of different parameters of a complex robot [7], or automating the novel design and manufacturing process of robots with functional materials [8, 9]. In all of these studies, intentionally introducing stochasticity in the process improved the capability of the underlying application. Stochasticity may result in a favorable outcome where adaptation means reliability and compliance by exploring. However, it may lead to an unfavorable outcome when precision is required [10, 11].

The field of soft robotics lies at the intersection of mechanical engineering, material science and a combination of control theory and computer science. Soft robots are compliant, adaptable, and safe to interact with. With compliance and softness also comes the stochasticity in their behavior. The stochasticity here refers to the inherent variability and unpredictability in their movements and responses to external environment. Since soft robots are made up of flexible material, their stochasticity is traditionally considered a consequence of the plastic properties of the materials such as damping, hysteresis, nonlinear deformations, etc. However, there are additional factors that may contribute to the behavioral stochasticity, such as varying environmental conditions like temperature, humidity, pressure, manufacturing inaccuracies, varying moment of inertia due to imbalanced morphology, etc.

When it comes to the precision requirements for soft robot applications, such as delicate surgeries [12] or mimicking a biological phenomena learned from a biological system [13], whether in modeling [14] or control [6, 10, 15], stochasticity may lead to unfavorable outcomes primarily due to the factors that make this class of robotics advantageous i.e., variability, compliance, and unpredictability. Additionally, the control solutions that are inherently robust in nature like, Reinforcement Learning (RL)-based algorithms, tend to underperform with systems that exhibit stochastic behavior [6, 10], introducing additional challenges to the soft robots' control field and therefore requires more sophisticated and resource intensive solutions [16]. The unpredictability also increases the safety risks associated with the robot's own morphology and the intended application environment.

The stochasticity introduced in the behaviors of soft robots, as perceived by control algorithms, can also stem from the sensing mechanisms employed to estimate their state feedback. Factors such as sensor noise, delays, inaccuracies, and the dynamic nature of environmental conditions contribute significantly to the stochastic behaviors observed [17]. For example, sensors may provide inconsistent feedback due to changes in temperature, humidity, or pressure, leading to variability in robot response [18, 19]. Moreover, the quality and precision of sensory mechanisms play a crucial role in how effectively control algorithms can adapt and manage robot behavior [20]. Thus, while the intrinsic stochasticity of soft robots can enhance adaptability and compliance, the additional layer of variability introduced by sensing mechanisms poses challenges in achieving precision and reliability in their control.

Another factor responsible for nonrepeatable behavior in soft robots, beyond the material and control solution, is the actuation mechanism. Traditionally, soft robotic platforms are actuated using fluidic channels, tendons/wires, Shape Memory Alloys (SMAs), or Magnetorheological Materials (MRs) [21, 22], etc. The mechanisms introduce variability of their own; For example, pneumatically driven soft robotic platforms include electronic pressure regulators, and they are known for their characteristic variable response [15]. The same pneumatic regulators usually do not include negative pressure regulators, which further introduce slow or incomplete depletion of the pneumatic channels. Similarly, other associated actuation-related stochastic responses come from the variable tensions in the tendons, slow and temperature-dependent response of SMAs and magnetic hysteresis of MRs, etc.

Based on the aforementioned points, it is evident that understanding the stochastic nature of the system is essential for identifying appropriate applications, control strategies, countermeasures, and compensation techniques for them to ensure consistent, reliable, and extended performance.

In this paper, we present our perspective on the link of the stochasticity-introducing factors contributing to the recorded change in the behavior of a soft continuum manipulator and, thus, the validity of a control solution over its useful lifetime. Finally, potential remedies for addressing stochasticity in terms of control solutions are discussed, along with the impending challenges and additional factors to consider to achieve desired response.

2. Stochasticity Analysis

It is important to understand the contributing factors of stochasticity in soft robots in order to optimize the phases of their design and operation. The main reason behind the inconsistency in the behavior of soft robots is the material that is used for their fabrication. These materials are mainly composed of very flexible elastomers that are sensitive to a number of elements, as discussed below.

2.1. Material Induced Stochasticity in Soft Robots

2.1.1. Temporal behavioral variations As elastomers age, they undergo changes. Over time, their physical attributes, such as their resilience to stress and flexibility, may deteriorate. A

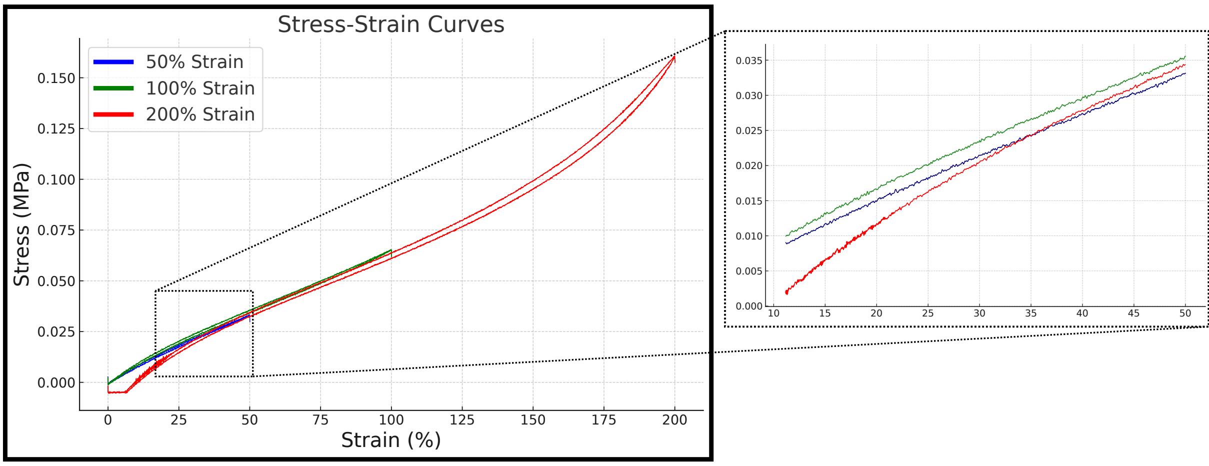

Figure 1. Stress-strain curves for Ecoflex 50 Tensile Sample; If actuators in a robot have been characterised against different levels of strain (for e.g at 50%, 100%, 200%) but then during operation have to operate at same levels of strain (for e.g 30%), there behavior would be different as can be seen from the magnified image.

robot could be impacted by it by becoming less predictable during operation.

2.1.2. Strain-induced variability This refers to the variations that occur as a result of mechanical deformation or stress. When subjected to different strains, the elastomers change their behaviour which makes it challenging to precisely forecast their reaction to changing loads particularly in dynamic scenarios, due to their nonlinear characteristics.

The strain induced variability can be observed through an example. Figure 1 shows the results of a tensile test that was conducted using an Instron (Universal Testing Machine) on a standard Ecoflex 50 tensile sample (ASTM D412). Three different samples were used in the experiment, and each of them was subjected to three different levels of strain: 50%, 100%, and 200%. Four tests were performed on each sample for each strain at a constant speed of 50 mm/min. The first cycle was ignored to account for Mullin's effect. The average of the second, third, and fourth cycles has been plotted for each curve.

From the figure, it is clear that the sample's material characteristics cause it to show hysteresis. Moreover, there are behavioural changes in response to varying strain levels. It is clear from a close inspection of every curve that the stress response differs for every one of them at the same strain value. Understanding this behavior is important to understand the stochastic nature of soft robots.

2.1.3. Temperature sensitivity Elastomers react strongly to temperature variations, in contrast to other materials. Environments with fluctuating temperatures can affect the overall mechanical properties of the elastomers. An example is that an elastomeric sample that is allowed to cure at room temperature displays different characteristics than the one cured at higher temperature.

2.1.4. Interaction with the surroundings The elastomers have a responsive behavior to their environment. The material properties of elastomers can undergo alterations as a result of exposure to various chemicals, moisture, and several other environmental factors. These changes have a direct impact on the overall performance of a soft robot.

2.1.5. Variations in mixing ratios Due to the fact that elastomers are commonly composed of a mixture of different chemicals, their synthesis depends on accurate mixing ratios. Fluctuations in the proportion of ingredients can influence the characteristics of the final result, leading to inconsistent results.

2.1.6. Shelf life and storage conditions Elastomeric materials can be influenced by factors such as light, air, temperature, and storage conditions, which can potentially impact their longevity. For instance, an elastomeric sample that is newly synthesized will have distinct characteristics compared to the one that has been stored for a period of time. It is important to maintain proper storage conditions to avoid compromising the material properties.

2.2. Stochasticity due to Wear and Degradation of Soft Robots

The unpredictability in soft robots' behavior can also arise due to their wear and degradation patterns. Its important to understand these stochastic aspects as it directly relates to the maintenance processes and robots' lifespan. Soft robots during their operation undergo complex motions and patterns unlike the rigid robots which can give rise to wear and tear over a period of time.Predictive maintenance should be performed in order to take into account this aspect of stochasticity.

2.3. Stochasticity due to Manufacturing Discrepancies

Three soft linear actuators internally reinforced with fibers made up of Dragon skin 10 shown in Figure 2a have been fabricated under exactly same conditions. When characterized against pressure, all three exhibited different behaviors (see Figure 2b). The main reason behind this is the human factor involved in the fabrication process. Although the same fabrication protocols were followed throughout the process, the fact that humans cannot replicate any two repeated steps with 100 percent accuracy leads to persistent challenges. In addition to the human error involved, the factors discussed in sections 2.1 and 2.2 contributed to the overall stochastic behavior of these actuators.

After the soft continuum manipulator was fully fabricated, testing its performance under the same actuation-space trajectories multiple times resulted in different task-space trajectories, as shown in Figure 3a. A population statistics was computed from the results where the very first trial conducted during the experiments (shown in red color in Figure 3a) was treated as a base trial. All the subsequent trials were compared with the base trial. It is important to note here that any trial out of six can be considered as a base trial. An error was computed in the individual axes (between the base trial and subsequent trials). The error (in mm) along y-axis is reported, for every trial along x-axis, as shown in Figure 3b, in the form of boxplots.

The factors responsible for the stochasticity in the soft manipulator may involve the incomplete depletion of the pneumatic chambers of the soft manipulator, variable moment of inertia along the length of the soft manipulator due to imbalanced morphology of the soft manipulator resulting from the actuators' fabrication discrepancies discussed in sections 2.1 and 2.2, and variable initial conditions (e.g., task-space tip position of the soft manipulator, etc.). We used motion capture systems (with error ≤ 0.5 mm) to record the soft robot movements which reduced the uncertainties due to the sensor.

2.4. Application Driven Stochasticity

Depending on the application where soft robots are deployed, the stochasticity can arise. An example can be the biomedical applications where soft robots interact with the tissues that are themselves stochastic in nature owing to their softness. When working in the areas of prosthetics, tissue engineering and other related fields, these stochastic interactions should be taken into account to better predict the behavior of soft robots during their operation.

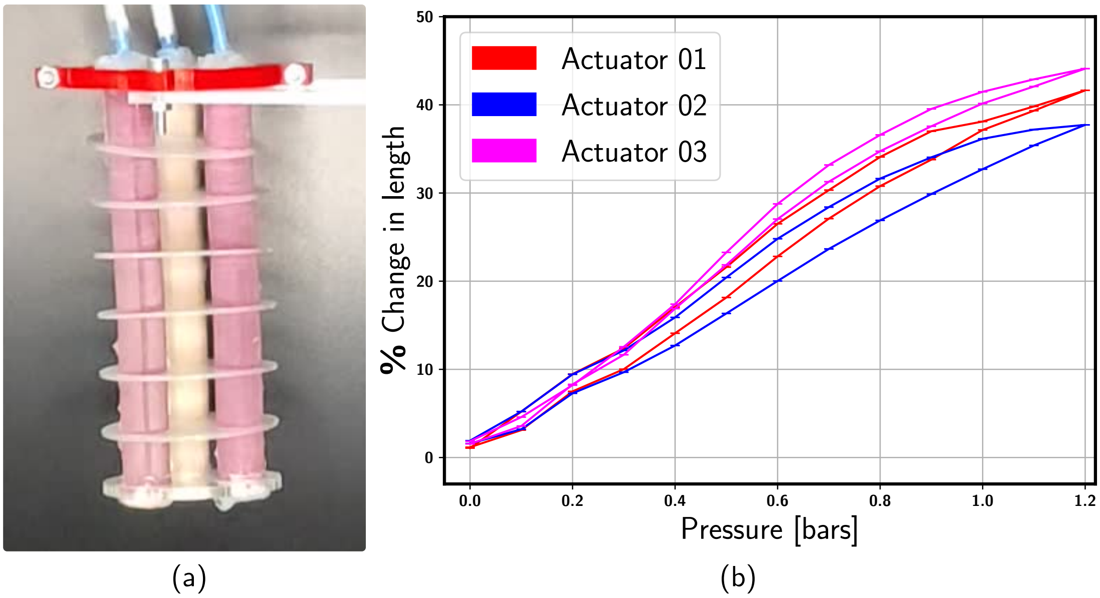

Figure 2. Three internally fiber reinforced soft linear actuators were designed with Dragon-Skin 10. A soft continuum manipulator with three-independently actuated linear actuators were combined to a single module, as shown in (a). The three linear actuators were individually characterized and the pressure vs percentage elongation of the three actuators is shown in (b).

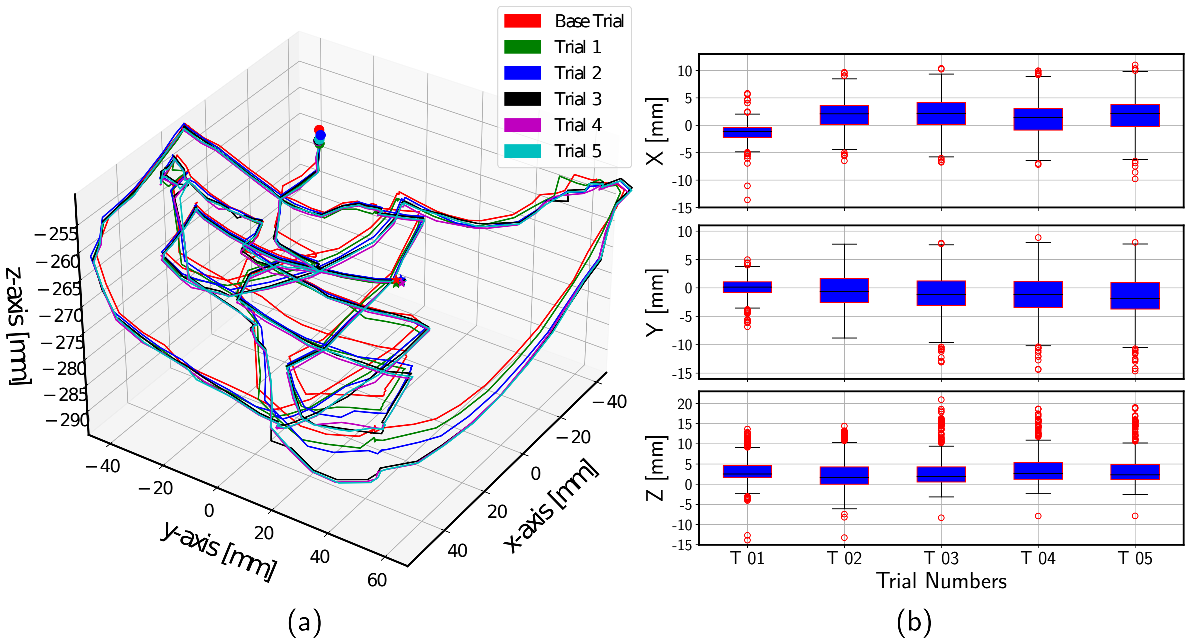

Figure 3. A single-module pneumatically actuated soft continuum manipulator, with three independently actuated pneumatic chambers, was actuated six times under the same actuation-space trajectory. The 3D task-space trajectories acquired from consecutive trials are shown in (a). The population statistics, for the error between the base trials (the first trial conducted during the experiments) and the following five trials, is shown in (b). The robot was actuated in the dynamics domain.

3. Effect on the Control of Soft Robots

In the literature, the control of soft robots is proposed in one of the three ways: type 1 — modeling the behavior of the underlying platform and deriving a control solution for it [23, 24, 25], type 2 — deriving a control solution directly on the physical platform [13, 26, 27, 28, 29], and type 3 — a combination of the two [10, 30, 31, 32]. However, it is acknowledged that deriving control solutions directly on a soft robot is a relatively underexplored area due to the complex and stochastic mechanics of soft robots.

When it comes to the modeling of soft robots, there have been numerous solutions [33], including Constant Curvature, Piecewise Constant Curvature, Piecewise Smooth Curvature, Koopman operators, Kirchhoff love shell theory, Euler Bernoulli beam theory, Cosserat rod theory, Finite Element Methods, Data-driven deep learning methods, etc. Most of the methods are capable of describing the soft robots' behavior and geometry in static, kinematic and dynamic domain. However, the validity of these approaches decreases when we move from the static to the dynamic domain. Many factors that remained dormant in the static (equilibrium) domain, or had time to settle when displaced from one point to another (such as hysteresis, forces, moment of inertia), do not enjoy the same luxury in the dynamic domain. Additionally, the factors, experimented upon in Section 2, are not necessarily addressed by the modeling approaches. Consequently, the solutions presented in type 1 and 2 suffer greatly and face a substantial sim2real performance gap [6, 10].

Type 2 solutions are usually learned using sample-efficient learning-based approaches [27, 34, 35]. It is imperative that these approaches learn from a limited dataset due to the fragile morphology of soft robots and that they are learned directly on the platform. Consequently, the control solutions do not exhibit sim2real performance gap [27, 13]. However, their robustness and adaptability to variability in the application environment or material changes within the soft platform itself can be questionable owing to the limited dataset used for learning. Additionally, if the morphology of the subject platform is not fragile, one may execute the online learning scheme for extended period. Doing so, as demonstrated in Section 2, may result in the soft robot undergoing change in its behavior due to the change in the material properties and by that extension, causing the solution to underperform. A similar trend was also observed for a tactile sensor undergoing change due to a change in its material properties as a result of overnight real-world data-driven model training [36].

This aspect also highlights a gap in the field of soft robot control. While many control solutions in the literature demonstrate good performance, there is a noticeable absence of discussions regarding the adaptability and repeatability of these solutions over an extended period. In essence, if a control solution proves effective initially, how likely it is to remain applicable after prolonged use of the soft platform or as the material ages? Interestingly, this aspect is extensively studied in sensor models, as sensors tend to introduce drift in their readings over time, models typically are made to reflect this drift in sensor readings [17].

4. Potential Solutions

Based on the control solutions listed in Section 3, stochasticity can be overcome through one of the three strategies: (1) With model improvements: a control solution is derived from a model that can account for either the global properties of the underlying soft platform and forecast any changes that may potentially occur during the lifetime of the soft platform or it is sub-optimal and undergoes improvements periodically. (2) From scratch again: whenever the soft platform undergoes a significant change in performance, a control solution is derived from scratch. (3) Compensatory agent: a compliant adaptor responsible for overcoming the performance gap on the top of a control solution.

4.1. With Model Improvements
Deriving a global model of a soft robot is not a practically feasible solution due to the attributes inherent to the soft structures and the variabilities in the material properties over time. However, a sub-optimal model of the behavior of a soft robot is possible. As expected the performance of this model may degrade over time which can be mitigated by periodically improving it as presented in our previous works [13, 27, 32]. In these works, a control solution is trained using Imitation learning (IL) with a behavioral map of the underlying soft manipulator in the dynamics domain. Since, the solution was trained using IL so its robustness against stochasticity and other variations needed improvements. Combining the IL-trained solution with a periodically improving dynamic behavioral map of the soft manipulator via Transfer Learning (TL) showed not only improved performance against stochasticity but also task repeatability with minimum standard deviation. While this approach proved to be sample efficient, it can only perform qualitatively. For quantitative response, a dynamic gait controller was presented in [34] that executes, periodically, a bootstrapping algorithm on an ensemble of dynamic gaits generated by a neural oscillator.

4.2. From Scratch Again
The strategy explores the possibility of deriving or training a control solution everytime the underlying platform undergoes significant changes. Such a technique is particularly useful when employed with a learning-based control strategy where the performance of the trained solution decreases drastically [37, 38] in response to the behavioral modification of the soft robot. However, such a solution can be sample inefficient and may also become impractical if the behavior of the soft platform varies more often owing to external conditions.

4.3. Compensatory Agent
This strategy is about deriving/training an additional agent whose job is to compensate for the performance gap. The examples of such schemes are presented in our previous works in [6, 10]. RL-trained policies tend to be robust; however, if the training environment undergoes variation, the performance degrades. We presented a compliant adaptor, learned completely in online mode with the soft robot, which can compensate for the training-to-reality gap, stochasticity, and performance degradation due to external stress affecting the soft robot's performance. Additionally, the performance of these schemes was also evaluated when one or more of the actuation channels of the soft robot were damaged. The compensator was able to adapt by using the redundancy present in the robot. However, such a scheme can only work as long as the task constraints are met. If there is a change in the soft robot behavior where the current task constraints become invalid, the compensator may consider it as a new task and won't be able to adapt to it.

Other similar works presented in the literature include combining a model-plant mismatch compensator with a Model Predictive Control (MPC), by Koryakovsky et al. [39], for a set-point-reaching task. However, the validity of the approach has been tested with a seven-DoF rigid robot. A similar approach in the kinematics domain was also presented by Kalidindi et al. [40] tested with the kinematic simulation environment of a soft manipulator. Johnson et al. [41] used a first-principles model combined with a data-driven model based on machine learning (ML) for the MPC-based controller. Their study showed a 52% increase in the controller's performance compared to four different models employed for the same task with the MPC. In addition to control strategies, the other aspects that can help reduce stochasticity in soft robots are discussed below.

4.4. Manufacturing and Quality Control
The stochasticity induced due to manufacturing processes can be reduced by taking appropriate measures for quality control. Some of the suggestions that can be taken into account in this regard are:

- Use fabrication techniques that involve minimum inaccuracies like 3D printing where applicable.
- Make sure to use the same composition of material everytime in order to avoid variability.
- Perform the fabrication in environment with controlled humidity and temperature.
- Regularly calibrate the equipment and standardize the procedures involved in fabrication.

4.5. Simulate Behavior of Soft Robots
Significant development has been made on simulating the behavior of soft robots in the last decade. Some of the notable simulators in this regard are SOFA, Deformable Gym, SoMoGym, Elastica and Chrono. Simulating the behavior of soft robots in these advanced simulation environments can significantly enhance the understanding of the system by providing deeper insights on their interactions with the objects and environment.

5. Challenges and Future Work
The stochasticity in soft robots is an unavoidable phenomenon which can be mitigated through standardized processes of material synthesis, fabrication methods and controlled environmental conditions but cannot be fully eradicated. This is owing to the fact that the factors involved in inducing the stochasticity cannot be controlled to the fullest. The human error involved in the fabrication processes, the softness induced material non-linearity and the fluctuating environmental conditions will always be there to play there role in introducing the inconsistency in soft robot's behavior. This poses a challenge to predict the exact behavior of soft robot during operation.

In order to acquire reliability in the operation of this class of robotics, it is imperative that the proposed control solutions actively account for the stochasticity and compensate for the variability. Presenting adaptable control solutions has a high impact in this domain because while the stochasticity answers the question about the variability that is available right now, how it will change over time is a factor we may not be able to predict. Continual learning paradigms are best known for their ability to adapt for extensive changes by using previous knowledge. These approaches are inspired by the learning capabilities of the human brain. In future, we would like to use these learning paradigms as compensatory factors or as substitutes for models with adaptive capabilities.

6. Conclusion
This paper discusses several factors that potentially contribute to the stochastic behavior of soft structures. This randomness in behavior cannot be eradicated to the fullest, but can be mitigated through careful considerations related to materials, manufacturing, and controls. Where, on one hand, stochasticity poses challenges in determining the exact behavior of soft robots, on the other hand, it can be seen as an opportunity in a way that the compliance and softness of the material helps the robot function in unstructured environments. It contributes to additional challenges in terms of their reliable and repeatable control. Therefore, we listed the factors that should be carefully considered when proposing their control solutions. Finally, we discussed the generic control schemes traditionally used with these robots and highlighted potential strategies to alleviate the performance gaps introduced by the inherent unpredictability.

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