Morphological Computation – A Potential Solution for the Control Problem in Soft Robotics

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Soft robotics provides a new and exciting approach to design robots. Often inspired by the remarkable performances of biological systems a number of soft robotic designs have been proposed and implemented. Despite their great potential with respect to safety, energy efficiency, and adaptivity, soft robotics still faces a number of fundamental problems, e.g. their inherent complex dynamics that makes it difficult to apply classical control approaches. Morphological computation, a concept that understands that physical bodies can carry out computation, has the great potential to overcome this challenge by providing a novel point of view. Recent theoretical models on morphological computation as well real-world proof of concepts suggest that these unwanted complex dynamics of soft bodies can be actually beneficial and that they can be exploited as a computational resource. As a result, morphological computation allows to simplify the control and learning tasks by outsourcing computation to the physical body and, therefore, pointing to a potential solution for the control problem in soft robotics.

Keywords: soft robotics; morphological computation; control; embodiment

1. Introduction

Soft robotics is an exciting new field of robotics that provides a fresh approach to designing intelligent systems. There exists no general definition for soft robotics, however, it is loosely accepted that it includes any type of robot that is build (at least partially) with soft materials. This ranges from completely soft silicone based structures like octopus arms[1] to more rigid actuation systems that are able to change their stiffness.[2]

Often, soft robots are directly inspired by biological systems, as "softness" is an inherent property of most animals and plants. Since biological systems widely outperform state-of-the-art robots in most tasks, it make sense to have a closer look at biological solutions for problems that roboticist are seeking to solve. Such problems include stable, dynamic locomotion in unknown terrain, energy efficient movements, adaptation to new tasks and environmental conditions, and dealing with unknown objects in the context of grasping – just to name a few. Intuitively, one can see that softness plays a role in all of these remarkable performances. To give an example from locomotion, the soft soles of the feet and the muscle tendon systems in the leg are able to negotiate with most of the "unevenness" of the ground purely on the mechanical level. They are also able to store and release energy, and during running they are even able to adapt their stiffness to counteract different stiffness in the ground to locomote at the most energy efficient level.[3] All of these remarkable features are carried out by the soft body. Biological systems have intelligent bodies and they are intelligent, partly, because they are soft.[4]

Based on these insight soft robotics has the great potential to provide better performing robots in a wide range of challenging tasks. In combination with the additional benefit of being potentially safer to interact, the soft robotic approach is highly relevant for the next generation of robots that should share with us our working and living spaces. However, despite this great potential, so far, soft robotics was not able to fulfill its promises. The reason is that the approach brings with it a range of problems that have to be solved before the "soft revolution" can take place.

One of the biggest challenges are the inherent complex dynamics that are typical for soft bodies. Compared to rigid robots, the body of soft structures exhibit a high dimensional state space, strongly nonlinear dynamics, under-actuation, and high redundancy. All these properties make it difficult to model such systems and, consequently, make them hard to control. Current robotic designs try to avoid these issues by using rigid body parts, high torque servo motors, and fully actuated systems. The resulting robots are predictable and easy to control with standard tools from control theory. However, as pointed out before, this approach fails completely at tasks where highly dynamic and complex interaction is needed.

By solving the "control problem" in soft robots classical control approaches have been pushed to their limits, see, e.g. Wittmeier et al.[5] Since soft robotics provide a radical new approach to design robots, we might have to consider also a radical new approach to control them as well. Recent theoretical results[6,7] as well real-world proof of concepts[1,8–10] suggest that morphological computation might be the solution that we are looking for. Instead of trying to suppress complex and nonlinear dynamics, we should embrace and exploit them for our needs.

2. Solving the Control Problem with Morphological Computation

Morphological computation is a concept that also has been inspired by biological systems. It is based on observations in animals, but also in plants, cellular structures and even down to the bio-molecular interactions, that morphology plays a crucial role in intelligent behavior. These observations suggest that physical bodies of biological systems are carrying out computations that are beneficial for their interactions with the environment. Something that can also be seen in the previously mentioned example of running. The mechanical structure (i.e. soft sole and muscle tendon system) is stabilizing the movement during dynamic locomotion without the need of being controlled by the brain.

As one can see by this example, we consider morphology not only to be the shape or form of the body. It includes also all physical parameters describing the dynamic behaviour, i.e. properties like stiffness, damping, friction, etc. Moreover, even the morphology of the environment plays a part of the computation as physical interaction always includes two sides, e.g. locomoting on ground or grasping an object.

Typically, morphological computation is applied in robotics only as a source of inspiration on how to design robots. However, in combination with engineering ingenuity and parameter tweaking a number of impressive robots have been produced.[11] Until recently there has been no theoretical foundation to support the approach. The work by Hauser et al.[6,7] was the first to provide theoretical frameworks to describe rigorously the computational power of physical bodies. The underlying idea is to understand the complex dynamics of a body as a computational resource that can be exploited.[12] Hauser et al.[6,7] demonstrated that this approach allows the implementation of a remarkable wide range of computations with the help of complex morphologies.

For example, robotic bodies can be exploited for tasks to nonlinearly process sensory input streams considering the history of input values (memory). This is useful, e.g. in the context of an intelligent, dynamic sensor with a morphology that is able to carry our some form of computational signal preprocessing. Another successfully demonstrated task was to emulate given complex, nonlinear differential equations. This shows the feasibility of an implementation of nonlinear controllers in the physical layer within the morphological computation approach. Hauser et al.[7] even produced highly stable and robust, nonlinear limit cycles, which are especially useful for locomotion.

However, the proposed morphological computation setup is even able to go one step further. It has been shown[7] that using morphology one can implement analog, finite state switching machines. For example, one can build a morphological setup that can produce robustly different nonlinear limit cycles, with the addition that a transition between them can be triggered by a simply change in external forces. This means the body is not only able to produce various useful signal for locomotion (e.g. different gaits), but it is also able to sense a change in the environment and switch accordingly.

The underlying idea of the theoretical models are based on a supervised machine learning technique called reservoir computing[13] (RC). It uses a randomly initialized network of nodes[a] to build a high-dimensional, nonlinear dynamical system, aka the *reservoir*. The sketch in the upper left corner of Figure 1 shows an example of a standard RC setup.

If such a reservoir is excited by some low-dimensional input (input stream), the reservoir responds by integrating these signals and combining and transforming them nonlinearily into its high-dimensional state space. The reservoir takes over the role of a *kernel* in a machine learning sense.[6] Due to this property it is sufficient to simply add linear readouts from the reservoir (see Figure 1) to get a powerful computational device. Without altering the reservoir itself, we can learn to emulate complex, dynamic representation (given as input output data set) by simply finding optimal linear, static readout weights.

The connection to morphological computation comes from the fact that reservoirs don't have to be in any specific form. In fact there exist different flavors[13] reflecting different ways to implement reservoirs. To be useful a reservoir simply needs to be a highly complex dynamical system. Looking at the bodies of biological systems and soft robots and their dynamics we can immediately see that they can serve as reservoirs. We simply have to add a readouts from their high-dimensional state space to exploit them as computational resources.

The remarkable conclusion is by exploiting the complex body dynamics of soft robots we can learn to emulate complex, nonlinear computations (like the examples given in the beginning of this section) by simply finding some linear and static output weights. Hence, the task to learn to emulate a nonlinear dynamical system is, with the help of the soft body, reduced to

[a]The nodes are typically modeled as simple, but nonlinear differential equations.

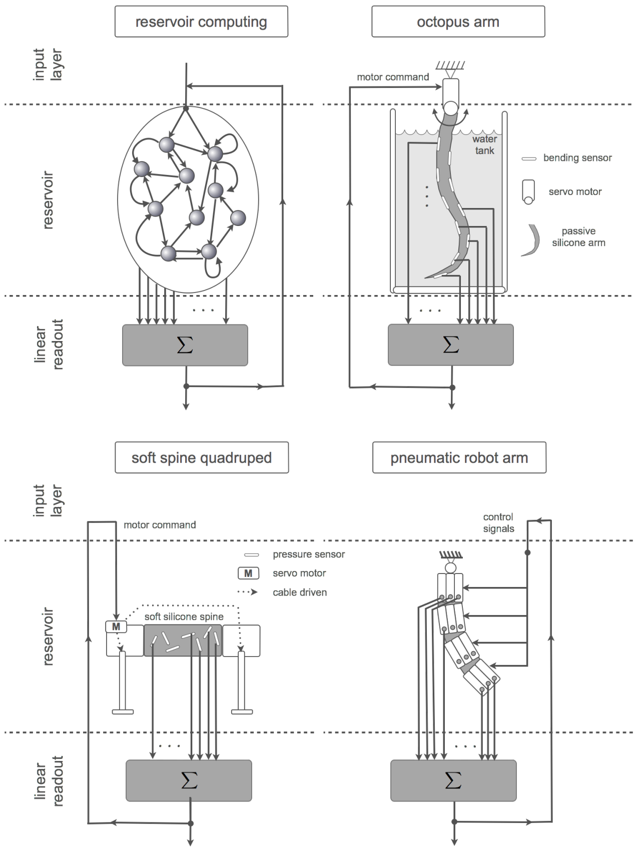

Fig. 1. Figure adapted from Hauser et al.[12] It shows the implementation of the reservoir computing approach (top/left) and it various implementation in morphological computation approaches; (top/right) is the octopus arm setup;[8] (bottom/left) the Kitty robot;[9] (bottom/right) a pneumatic, modular robot arm.[10]

simple linear regression.

If we are able to emulate, e.g. a nonlinear controller with this setup and consider that the readout is only linear and static, we can conclude that the part of the computation that is dynamic (memory) and nonlinear has to happen in the body. We can say in this case that nonlinearity and memory is outsourced to the physical body, which is exactly what morphological computation is all about.

Another remarkable implication of these theoretical models is the fact that they imply a paradigm shift in robot design. When asked which properties physical body should have to be computationally powerful, the models

provide a highly counterintuitive answer: To be computationally powerful a robot body should have a high-dimensional state space, exhibit nonlinearities, and should be compliant - even noise is beneficial. Note that all these properties are deliberately suppressed in rigid robot designs. However, they are inherently present in biological systems and, more importantly, they describe quite accurately soft bodied robots.
In summary, complex body dynamics of soft robots, which are normally seen as problematic, are from the view point of morphological computation beneficial, since they can be exploited as a computational resource. In the next section, we discuss a series of real-world setups demonstrating the applicability of this idea under real-world conditions.

3. Examples with Real-World Robots

Despite the fact that the approach is still new, there are already a number of platforms, which have been successfully used to show the applicability of the setup under real-world conditions.[8–10] All of them use different soft bodied structures as their reservoir ranging from an octopus inspired arm, to a compliant spine in a quadruped, to a pneumatically driven modular arm, compare Figures 1 and 2.

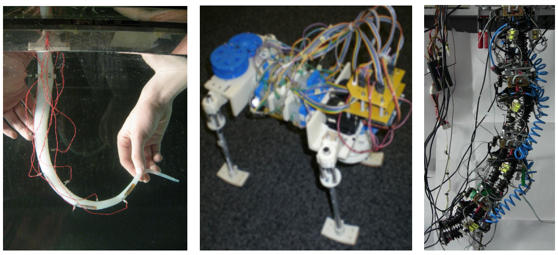

Fig. 2. Three different soft robotic platforms used to demonstrate the applicability of the approach in the real world. (left) a soft octopus arm;[8] (middle) quadruped with compliant spine;[9] (right) pneumatically driven modular robot arm[10]

There exist a series of publications using the artificial octopus arm of Figure 1 (top/right) and Figure 2 (left). The arm was made of silicone and is completely passive. It features 10 bending sensors distributed along the arm, five on each side, which serve as readout. The arm was attached to a rotational motor, which served as the input to the system. Nakajima et al. demonstrate with this platform that it can be used to carry out com-

putational tasks that included memory[8] and complex nonlinear dynamics.[1] They even showed that the octopus arm can be used to calculate a control signal to robustly control exactly the same arm.[8]
Another successful example is the Kitty robot,[9] see Figures 2 (middle) and 1 (bottom/left). Kitty is a quadruped robot that features a biologically inspired, compliant, multi-joint spine. Locomotion is induced by a single motor that bends the spine via a tendon system. In this case the reservoir was the compliant spine, which had 30 force sensors embedded forming the interface for the linear readout layer. Zhao et al. demonstrated that the setup can be used to produce robustly different behaviours for the robot like a bounding and trotting gait, and turning.
Finally, the concept has also been successfully applied to a robot arm designed to work in an industrial environment, see Figures 2 (right) and 1 (bottom/right). The arm[10] it pneumatically driven and comprises 4 equal and decentralized controlled segments, each with 3 actuated degrees of freedom and a total of 48 sensors, including stretch and pressure sensors, and accelerometers and gyroscopes. Again the morphological computation setup has been used successfully to harness the complex dynamics, in this case, to control the end point of the robot arm robustly along various desired trajectories.

4. Conclusion and Discussion

We have discussed the possibility of morphological computation being a solution for the control problem in soft robotics. The underlying idea is to embrace and exploit complex body dynamics as a computational resource. The idea is still new and, hence, there still remains a number of interesting research opportunities.
One of this interesting research question is which computational tasks should be outsourced to the body. While it seems to be quite obvious that, e.g. long-term planning would be best carried out in the "brain" of the robot, and reflexes are better implemented in the body, there is a large gray area in between to be explored.
Another question is related to the fact that in a morphological computation setup the physical properties of the body are representing the "programm" of the implemented functionality. So, if we want to change the functionality, we would have to change the body[b]. Recent results that use the concept of

[b]Note that if the body as a reservoir is complex enough, the change of the linear readout is often sufficient. Actually, Hauser et al.[6] showed that multiple computations can be

morphosis (adaptive morphology)[14] point to the possibility of highly versatile morphologies by using the right design. Another possibility is to learn to change to adapt the morphology, e.g. Hermans et al.[15] This type of approach will be even more important in the future when artificially growing and self healing systems will be available.

References

1. K. Nakajima, H. Hauser, T. Li and R. Pfeifer, *Scientific Reports* **5** (2015).
2. B. Vanderborght et al., *Robotics and Autonomous Systems* **61**, 1601 (2013).
3. H. Vu Quy, H. Hauser, D. Leach and R. Pfeifer, A variable stiffness mechanism for improving energy efficiency of a planar single-legged hopping robot, in *Advanced Robotics (ICAR), 2013 16th International Conference on*, Nov 2013.
4. R. Pfeifer, M. Lungarella and F. Iida, *Commun. ACM* **55**, 76(November 2012).
5. S. Wittmeier, C. Alessandro, N. Bascarevic, K. Dalamagkidis, D. Devereux, A. Diamond, M. Jäntsch, K. Jovanovic, R. Knight, H. G. Marques *et al.*, *Artificial Life* **19**, 171 (2013).
6. H. Hauser, A. Ijspeert, R. Füchslin, R. Pfeifer and W. Maass, *Biological Cybernetics* **105**, 355 (2011), Issue 5.
7. H. Hauser, A. Ijspeert, R. Füchslin, R. Pfeifer and W. Maass, *Biological Cybernetics* **106**, 1 (2012).
8. K. Nakajima, T. Li, H. Hauser and R. Pfeifer, *Journal of The Royal Society Interface* **11**, p. 20140437 (2014).
9. Q. Zhao, K. Nakajima, H. Sumioka, H. Hauser, R. Pfeifer, Spine Dynamics As a Computational Resource in Spine-Driven Quadruped Locomotion, in *IEEE/RSJ (IROS)*, 2013.
10. M. Eder, F. Hisch and H. Hauser, *in preparation* (2016).
11. R. Pfeifer and J. C. Bongard, *How the Body Shapes the Way we Think* (The MIT Press, 2006).
12. H. Hauser, K. Nakajima and R. M. Füchslin, Morphological computation – the body as a computational resource, in *E-book on Opinions and Outlooks on Morphological Computation*, eds. H. Hauser, R. M. Füchslin and R. Pfeifer, 2014) pp. 226–244.
13. B. Schrauwen, D. Verstraeten and J. Van Campenhout, An overview of reservoirx computing: theory, applications and implementations, in *Proceedings of the 15th European Symposium on Artificial Neural Networks*, 2007.
14. F. Corucci, M. Calisti, H. Hauser and C. Laschi, Novelty-based evolutionary design of morphing underwater robots, in *Proceedings of the 2015 on Genetic and Evolutionary Computation Conference*, 2015.
15. M. Hermans, B. Schrauwen, P. Bienstman and J. Dambre, *PLoS ONE* **9**, p. e86696 (2014).

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carried out by one morphology at the same time.