Learning-based Control Strategies for Soft Robots: Theory, Achievements and Future Challenges

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I. Introduction

Soft robots are built with soft materials, with low Young's modulus, or with materials that are not soft per se, but are arranged in highly deformable geometries [1]. Soft robots exist today over a wide range of morphologies (arms, fingers, legs, fins, ...), scales (from few mm to few m), abilities (reaching, grasping, walking, morphing, growing, swimming, jumping, crawling, digging, ...) and intended applications (in the biomedical field, underwater, in industry, ...). For the sake of clarity, we may focus here on the common case of soft robot arms (see Figure 1 as a reference), despite our description is intended to be completely general. Soft robot actuators have to deform the soft body, often in a continuum way. Similarly, sensors for soft robots are distributed in the soft structure and detect deformations induced by external forces, as well as those generated by robot actuators. Smart materials are used in soft robotics, like EAPs and SMAs, as well as fluidic actuation and other custom technologies. Soft robots are deformed by external forces, and this is designed to help their intended movements, according to the embodied intelligence paradigm, by which adaptive behaviour emerges from the physical interaction of the body with the environment. Control is delegated in part to the physical body, that performs morphological computation [2]. In other words, a very short control loop is closed at the mechanical level, on the motor system, through a mechanical feedback. Building robots that can accept such mechanical feedback from the environment is the main motivation for soft robotics. ~~Control is simplified in terms of computation and number of control variables.~~

Soft robots present extremely interesting control problems, which may benefit from learning-based approaches. Learning-based approaches are especially helpful when analytical models are hard to obtain, due to the complexity of robot ~~bodies~~kinematics and dynamics and their presence in unstructured environments, as in the case of soft robotics. Figure 2 reports data on publications in soft robotics, soft robot control and the use of learning in soft robot control, starting from 2005, when first papers on learning-based control of soft robots appeared. A general increase is visible, at different paces, though. Figure 3 shows the relative trends. The use of learning in soft robot control is growing, with

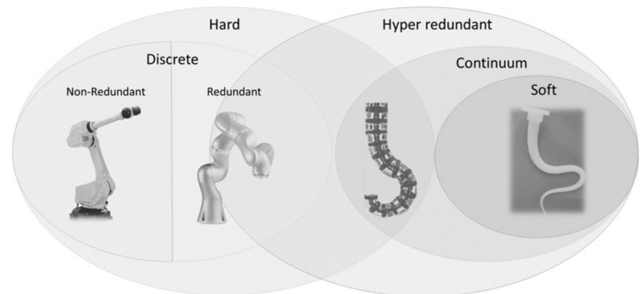

Fig. 1. ~~Evolution of DoFs with the robot structure~~An example of soft robot arm, on the right, with reference to other categories of robot arms, classified by their number of degrees of freedom (DOFs) (reprinted with permission from [3]).

a trend which is almost stable with respect to the general growth of the soft robotics field. The trend is similar to the use of learning in robot control, in general. We can also see a slight increase of attention of the control community to the control of soft robots, but with respect to the fast growth of soft robotics, soft robot control is not keeping pace, outlining important opportunities for the control community in this field. A clear growing trend instead is visible in the use of learning in soft robot control, within the control of soft robots (data from Scopus, 22/02/2022, with searches in Article Title, Abstract, Keywords; search keys reported in figure legends). The reason why more learning-based controllers have been applied in soft robotics may be due to both the availability of more powerful learning models and the difficulty of providing analytical models for such kinds of robots. ~~shows how in the recent few years there is an increasing trend of papers that employ learning-based control strategies (The data is collected from Scopus with keyword search from the Abstract and Title on Januray 31, 2022) shows an increasing production of papers on soft robot control and the use of learning methods~~.

In fact, learning has been used in robot control for years and we are recalling the basics of learning-based control in robotics in the next section. We then analyse the control challenges in soft robotics and the methods used for soft robot modeling, before presenting the achievements in learning-based control of soft robots. We do not have the ambition of providing a thorough picture of the state of this field, but we aim at going through the main achievements, seen as milestones in the progress of the field, as in the authors' experience. This is going to project us into the next challenges, with the aim of outlining the opportunities for research on control theory and systems applied to soft

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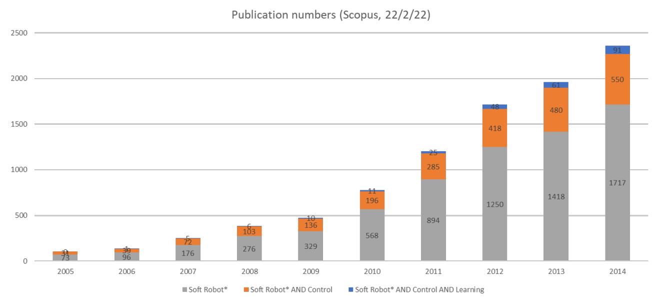

Fig. 2. The number of publications~~Interest~~ in soft robotics control have steadily risen over the years. A part of them addresses control problems in soft robotics. In this context, learning-approaches control strategies seem to be gaining popularity, in the last few years. ~~with a relatively even distribution among learning-based and model-based control. A significant portion of machine learning papers in soft robotics are focusing on solving the control problem.~~

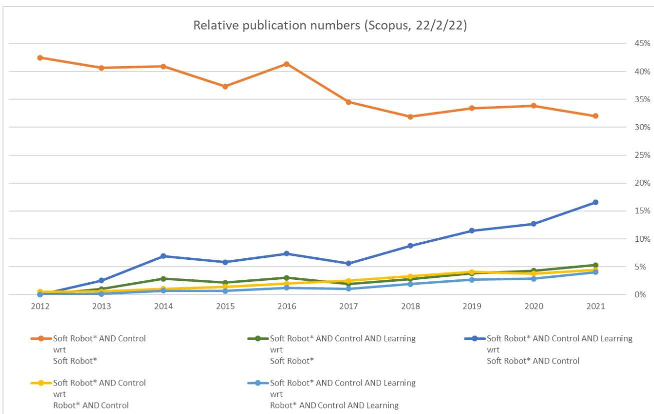

Fig. 3. Relative growth of publications. While an almost stable trend is visible in learning-based control within soft robotics, similar to the use of learning in robot control, a more significant growth is visible in the use of learning for soft robot control, among soft robot control publications. Margins for growth exist within the robot control community for addressing soft robotics challenges.

robotics.

II. Machine Learning for Robot Control

A. *Rationale*

Classical robotic controllers rely on analytical models that are based on geometric and physical insights. Machine Learning (ML) approaches represent a valid alternative to manual and pre-programmed ~~behaviours based on~~ analytical models. With ML, the models are estimated through experience, while the robot is interacting with the environment [4]. The basic idea is that the information can be extracted from sensory data acquired by the robot and used to build models. Non-linearities can be directly taken into account. More specifically, ML algorithms build a model based on sample data, known as "training data", allowing to make predictions without being explicitly programmed to do so. These predictions are used in robotics to estimate different models of the robot body or the environment.

First approaches to the use of ML in robot control focused on adaptive self-tuning control that consists of methods where ~~open~~ the parameters to set in an analytical model are derived with learning mechanisms. ~~However~~ Since it is not always possible to derive optimal parameters from data, controllers were then proposed, which embed model learning without any analytical definition. The idea is that, to derive the system behaviour, i.e. what is the effect of actions, information about states and actions are used. ML methods are used because these information can be accessible/available only partially, so it is needed to derive them from experience and provide predictions of missing information to generate appropriate actions (control policies).

ML techniques have shown to be effective in a variety of applications in robot control, such as tuning analytical model parameters, building inverse dynamics models [5] or inverse kinematics models [6], modelling the actuation of grippers for robot manipulation control [7], finding the relations between leg movements and locomotion [8], navigation [9] and disturbance rejection [10], as they enable straightforward model approximation.

B. ~~*Machine Learning for robot control*~~ *Learning tasks in robot control*

Learning-based controllers for robots usually approximate two kinds of models: (~~i~~1) the forward model that estimates the next state of a dynamic system based on current state and inputs and (~~ii~~2) the inverse model that predicts the inputs needed to move from the current state to the next desired state [11].

1) Forward models: Forward models represent the causal relation between system state and inputs [12]. Such a model would aim to mimic or represent the normal behaviour of the motor system in response to outgoing motor commands. For example, a forward model of the arm's dynamics might have as input a current state (e.g. join angles and velocities) and motor commands being issued by the controller and produce as output an estimation of the new state. However the state may or may not be accurately known by the controller and so one needs to separate the state variables from the sensed variables. Such a sensory output model would therefore have as input the current state and as output the predicted sensory feedback. By cascading a forward dynamics and a forward sensory output model, an estimation of the sensory consequences of a motor command can be achieved (feedforward model) [13].
Several examples in literature rely on supervised (including neural networks or standard regression) or unsupervised approaches to estimate the forward model. The first application of forward models for control is the Smith predictor [14], where the forward model is used to reject the effects of delays resulting from the feedback loop. Later, forward models found a wide application in Model Predictive Control (MPC) [15]. MPC computes optimal actions by minimizing a given cost function over a certain prediction horizon in the future. These predictions are

generated by using the forward model.

2) Inverse models: Inverse models invert the causal flow of the motor system. These models therefore also encapsulate knowledge about the behaviour of the motor system by predicting the actions required to move the systems from the current state to a desired future state. Learning inverse models may not be always possible when data space are not convex. For control, applications of inverse models can be traditionally found in computed torque robot control, where the inverse dynamics model is used to predict the torques needed to follow a trajectory in the joint space [5].
More complex models can be also learned and are used in complex tasks, like control of humanoid robots, where a task-space inverse dynamic model is needed to stabilize the center of mass of the robot [16].

C. From robotics to soft robotics

For rigid robots, the models discussed so far are based on the transformation from actuation space to joint space (and viceversa), which is easily obtained through the use of sensors (e.g. encoders mounted on electric motors), and on the trasformation from joint space to task space (and viceversa). In soft robotics, each of these transformations is more complex. Since soft robots are ideally continuum robots, actuators generate a deformation that in turn modifies the position in task space. An additional space (the configuration space) is introduced to describe the deformation, e.g. the arc parameters. The continuum robot kinematics can be decomposed into two submappings. One is between actuator space and configuration space, while the other is between this configuration space and task space (i.e. position and pose of the end-effector) [3]. Learning models are often used for directly estimating the mapping between actuation space and task space, but they can also replace intermediate transformations, e.g. between task space and configuration space.

III. Soft Robot as a control problem

Due to their flexible, deformable, and adaptive characteristics [17], soft robots have complex and unpredictable behaviors that affect modeling and control by introducing non-linearities and hysteresis [18]. Since soft robots are made of continuously deformable materials, their full state is governed by continuum mechanics rather than rigid-body dynamics. This results in systems with infinite degrees of freedom (DOFs) (see Figure 1) and their dynamics is often highly nonlinear. They do not have an infinity of actuators to control each of the DOFs, though. Thus, from a control point of view, soft robots are considered to be under-actuated systems. The goal is to use a ~~determined~~ finite number of actuators to control ~~continnum segments of these type of robots~~ infinite DOFs of the soft robot. ~~From a control point of view, the soft robot is said a system, whenever we are able to distinguish between its finite inputs and outputs with its infinite DoFs, linked by a causal relationship (Figure 3).~~ Thus, a soft robot with infinite DOFs is said to be an input-output (I/O) system in the sense of control theory, when it is possible to distinguish a causal relationship between finite controllable inputs and measurable or observable outputs.

The physical quantities of inputs, outputs and disturbances are finite and can describe the voltage, current, pressure, position, speed, external forces, or other actuation inputs. We can distinguish:
• direct actions, called control time inputs, ~~denoted $U_n(t)$,~~
• indirect actions, called disturbances~~, denoted $d_L(t)$,~~
• consequences of direct and indirect actions, called outputs.. ~~, denoted $y_k(t)$, Despite the large size of DoFs of the soft robot system (Figure 3)~~,
These variables alone are not sufficient to characterize the time evolution of the soft robot, where it is necessary to add the state variables [19]. These describe the internal memory variables of the soft robot system [20]. An efficient control of a continuum soft robot allows not only tracking desired targets like in conventional rigid robots, but also controlling optimally its shape in order to reproduce the desired behavior with a minimum energy consumption. For this purpose a Reduced Order Model (ROM) of the soft robot is suggested to reconstruct the optimal shapes using parametric curves modeling [21] with their advantages regarding boundaries and energy minimization. Thus, a shape control with a finite number of control points of the representative curve of the soft robot shape can be applied [22] with respect to time costs and accuracy performances.
Figure 4 depicts an example of a closed-loop control for a soft continuum manipulator, made up of 6 tubes of 16 vertebrae each, made from polyamide material. Each vertebra has 3 DOFs. To control such a robot, we have 6 electro-pneumatic actuator inputs and 6 measurable outputs corresponding to the lengths of tubes. The objective is to control the position of the tip of the soft manipulator. For this, it is possible to design a closed-loop control by deducing the elongations of the tubes from the Cartesian coordinates of the tip from the inverse kinematic model of the robot, then by converting the elongations into pressure, in order to control the pressures at low level from piezoelectric valves. The image of the tube lengths of the robot in voltage is calculated from the potentiometer wires. Finally, the Cartesian coordinates of the tip are calculated from the direct kinematic model for the position control. It is possible to reconstruct the shape of the soft continuum manipulator using a motion tracker system, which is an external set of cameras able to track markers placed along the robot.

IV. Models for soft robot systems

The synthesis of a control law for a soft robot requires a model~~s of~~, derived from the causal relations ~~discussed~~between the input-output (I/O) of the system, which describes the robot behavi~~o~~r. We are discussing such models in general terms, assuming an arm-like soft robot, made of soft materials and actuated by cables, fluidic chambers, or similar bending actuators, well aware that the modeling approaches may vary for different designs of soft robots,

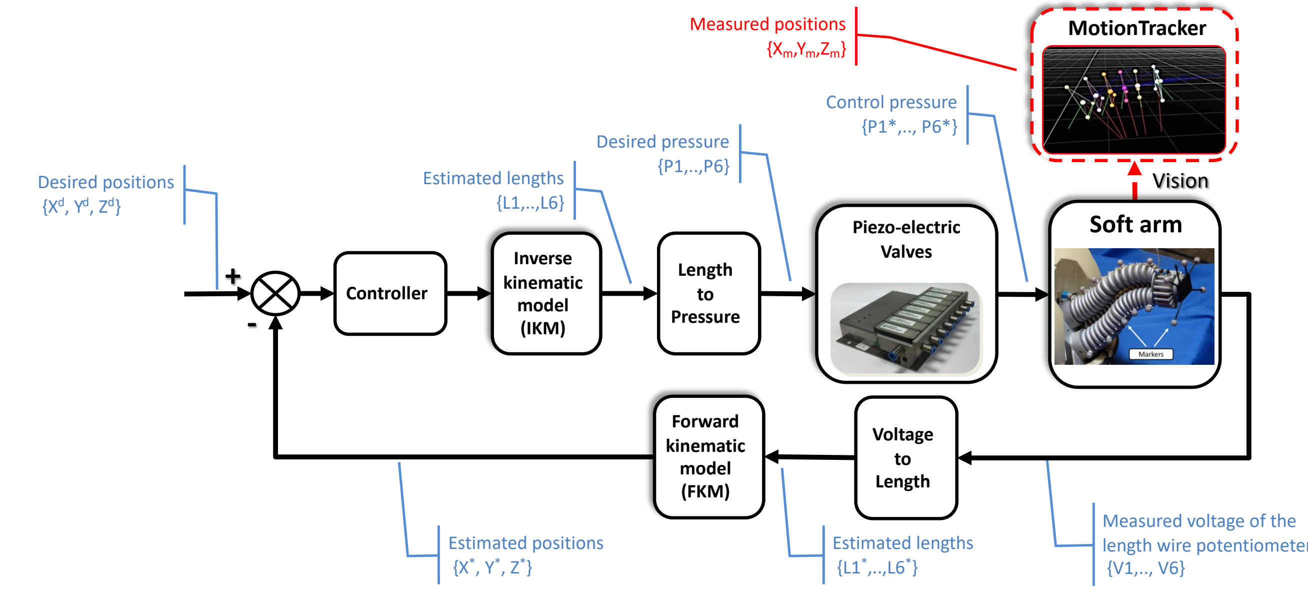

Fig. 4. Example of closed-loop Cartesian position control of a soft continuum manipulator

especially if we consider fabrics and/or smart materials. The relation that we model can be kinematic or dynamic. The infinite number of DOFs makes it complex to model a soft robot, without being able to achieve reductions and simplifications~~it without considering assumptions per task~~. So, it is possible to limit the number of DOFs but keeping the soft robot behaviour approaching a hyper-redundant structure. ~~The search for a mathematical~~Model of a soft robot system is described in literature according to three approaches. The first is called quantitative modeling approaches and consists in formulating mathematically a relationship between the causes and effects by using kinematic and dynamic fundamental equations. They usually suffer from several assumptions which yield inaccurate models, and one generally faces time-consuming or mathematical intractable issues to deduce the Inverse Kinematic Model (IKM) directly from the Forward Kinematic Model (FKM). These models are said “knowledge” models. This ~~The first one~~ assumes that it is possible to obtain an almost perfect description of the behavior of the soft robot system in kinematics [23] and dynamics [24] and [25]. ~~This is done by using a set of equations resulting from the application of the law of physics. The model thus obtained is said to be “knowledge”~~. Considering the infinite dimension of the DOFs of the soft robot, the model equations often remain complex to solve numerically. One of the possible solutions consists in reducing the size of this model while preserving the desired inputs and outputs (I/O) behavior. Thus, computational mechanics modeling has been used, based on the Finite Element Method (FEM), with a technique for the approximation of differential equations with boundary conditions. FEM has been used to discretize the theoretical infinite number of DOFs of soft robots [26]. The second approach ~~consists in finding parametric relations, describing the behaviour between the I/O of the soft robot system through learning, in relation to the measurements available and the number of tests carried out [23].~~is called qualitative modeling approaches or data-learning based approaches, consist in dividing the parameter space of the model into several classes according to the well-known operating modes, and then determining by learning the mathematical relations between the effects (sensor measurements of Cartesian or joint positions), and causes (inputs of voltage, pressure,.... Generally, these approaches are suffering from the explosion of the learning data-set which increases with the number of DOFs; and it is often difficult to establish well-structured control laws [27]. These~~This~~ models are said “black box” models. Depending on the number of DOFs of a soft robot, the learning phase that can build a relationship between inputs and outputs can be costly in computing time, ranging from hours to days, without forgetting the fatigue of the material of the soft robot. However, when the learning phase leads to a perfect reconstruction of the I/O behavior, the real-time implementation of the model remains efficient. The third approach~~combines the two previous approaches: the behavior of the soft robot is modeled by physical equations, but the resolution of the latter is done by approximation of black box models. This type of model~~ is called “hybrid”~~model [24].~~ and combines the advantages of quantitative and qualitative approaches. The idea is to build a mathematical model of the soft robot and to improve the model accuracy by identifying certain non-linearities using a qualitative approach. The main advantage of the hybrid approach is the ability to generate the learning data-set directly from the mathematical model. Also, it can reconstruct the robot shape in real-time [28].

In this context, ROM techniques are used to describe the state space reduction of continuous and bounded soft robots with high dimensions. The discretization of their kinematic chain is needed to simplify the solving of their representative differential equations, thanks to a low dimensional space. To design a ROM based controller of soft robot, the reduction of the state space are required to adapt the control to a specific mode. For that, several modal-based approaches for control have been developed, such as the eigenvalues-based technique for linearized systems [29], power expansion series approximation [28], space parametrization for shape control [30] and dynamical feedback controller to stabilize a desired trajectory in the curvature space [31]. From the other side, Model-Order-Reduction (MOR) has been introduced to simplify the complexity of the soft robot in terms of dimension and computational cost [32]. In this case, MOR techniques are used to reduce the state space dimension of existing soft robot Finite Element Method (FEM) model. MOR, unlike ROM, is not a modeling technique but a computational method. It can be used to represent the full-order dynamics model by using a linearized FEM model around an equilibrium point [33]. This has enabled the formulation of a stable observer and controller for the reduced and linearized system.

V. Achievements in Learning-Based Approaches for Soft Robot Control

Efforts for the control of soft robots based on ~~machine learning~~ ML have addressed different levels of encoding of robot models that, in turn, produced different control strategies. These can be classified according to the operating space:

1) Low level: actuation/joint space (e.g. cable length, pneumatic chamber control, others)
2) High-Level: task/configuration space (e.g. end effector control)
    a) Static (kinematic) model
    b) Dynamic model

~~The deformability of soft robots provides them with embodied intelligence which makes adaptive behaviour emerge from interaction with the environment. It simplifies low-level control and sensing issues, but complicates the high-level planning, control, and modelling of these systems. Machine learning approaches are being used as a valuable solution for the estimation of state representation of soft robots.~~ High-level control strategies can include the learning of either the static (kinematic) model or the dynamic model of the robot. A static model is time invariant and relies on the steady-state assumption: under force equilibrium the configuration of the manipulator has a lower dimension. Dynamic models, instead, are time-dependent and consider task space variable velocities. Learning mechanism are used to learn the mapping between the actuation/joint space and the task space both in static and dynamic conditions. These learning models are mainly based on supervised and reinforcement learning techniques (see sidebar I). Supervised learning is used when the behavior is observable: this means that data can be labelled. A typical way to use supervised learning is to let the robot explore the workspace (statically, by relying on the steady state assumption, or dynamically considering task space variable velocities) by using random movements (motor babbling) and save data that link actuation to task space. With these data, batch models (e.g. feed forward neural networks or recurrent neural networks) are trained to learn the forward or inverse mapping to be embedded in controllers. Reinforcement learning does not need to have labelled data. It allows to discover and learn the control policy thanks to the exploration capability that is not a feature of supervised learning. This makes reinforcement learning suitable for for complex tasks, that involve interaction with the environment.

Several important milestones have been achieved in the last 10 years in the control of soft robots. Figure ~~(see Fig.~~ 5~~)~~. gives a qualitative view of the growth of knowledge along these two mainstreams. We argue that they have similar trends, translated in time, and that we can expect a growth for dynamic control soon. A more detailed analysis of current approaches for controlling soft manipulators and a survey of current achievements are reported in [3].

A. Kinematic controllers

A first step in exploring a model-free approach to a static controller was proposed in [34]. This approach consists in learning the inverse static model of a non-redundant soft robot based on a feed-forward neural network. An important achievement for showing how the neural control system can take into account the variability of the arm with no effect on the performance was given by its experimental validation in comparison to the performance of an inverse Jacobian approach [35]. Further progress of this approach consists of the adoption of further learning techniques, like learning the inverse kinematics model by using local mappings of the differential inverse kinematics [36]. This model embedded in a feedback controller, allowed for redundancy resolution and adaptation to external disturbances. Lee and colleagues [37] took a step forward, by presenting a closed-loop inverse kinematic controller capable of online learning. It is based on locally weighted projection regression (LWPR) algorithm that allows to maintain control accuracy under external dynamic disturbance. However, all the above mentioned works learn a fixed solution to the IK problem, among all the infinite possbile redundant configurations. This restricts their use to just reaching tasks without the ability to plan trajectories in the configuration space. An evolution on the same line is the use of a reinforcement learning framework to solve the inverse kinematics problem, leading to a controller able to reach valuable results with high level of accuracy [38]. Building on that, a controller based on a reinforcement learning approach was built, capable of optimizing multiple objectives to learn deterministic stationary policies for position and stiffness control of a soft robot arm [39]. This work relies on a discrete state-space model and a straightforward extension would be extend the approach to a continuous space.

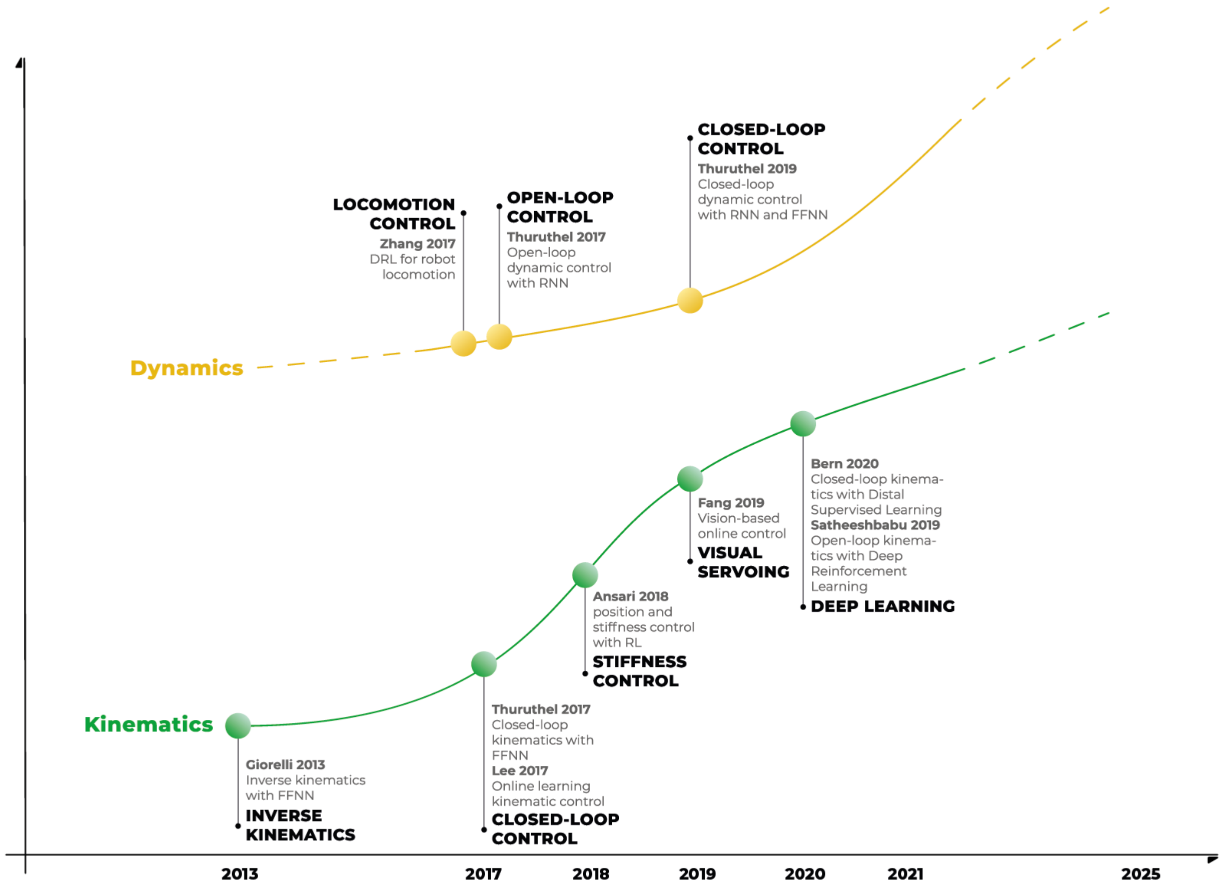

Fig. 5. Milestones of learning-based soft robot control, in kinematics and dynamics. The evolution of kinematics learning-based control systems started earlier and grew at a fast pace, but it is reaching a steady state. Learning-based dynamic controllers are having a recent progress, but they show a similar trend, just translated in time, outlining~~. with~~ perspectives for steep growth in the near future, by addressing the open challenges described in Section V.

The first visual servoing application for soft robots came one year later, from Fang and colleagues [40]. The proposed controller is able to learn the inverse mapping from collected camera images and refine this mapping online by using the Local Gaussian process regression algorithm. More recently, further progress is going in the direction of using deep learning [41]. ~~The first work consists of a distal learning method used for designing an open-loop control for a soft manipulator~~ This work learns the inverse static model of a soft manipulator using Deep Deterministic Policy Gradient (DDPG) for end effector path tracking. The latest few works in the field of kinematic control studies the use of differentiable learned models [42] and real-time adaptive models [43]. Differentiable models can reduce the computational effort for estimating control solutions, but is yet to be extended to a more complex system or for fully dynamic control. Online estimation of IK parameters are well suited for robotic systems that have a variable morphology, but reling solely on online data increases the control time and adds futher restrictions on the sensory system. Combining offline and online models is an alternate research direction yet to be investigated.

B. Dynamic controllers

Dynamic controllers have been recently proposed based on model-free methods. In 2017, Zhang and colleagues [44] presented the first dynamic model with application to locomotion. In the same year, Thuruthel and colleagues [45] used a recurrent neural network for the learning of the forward dynamic model in conjunction with trajectory optimization for a soft manipulator. The proposed controller was able to follow predefined trajectories with high speed and accuracy. However, the controller was still open-loop because of the computational time required to solve the optimization problem. This challenge was addressed in [46] albeit on a single soft joint. To overcome limitations due to open loop control, a model-based policy learning method for the closed-loop dynamic control of a soft robotic manipulator using was proposed [47]. ~~The representation of the policy architecture allows for the stability of the controller with respect to changes in the control frequency, sensory noise, and dynamics. An analysis of current approaches for controlling soft manipulators and a survey of current achievements are reported in [3].~~

VI. CHALLENGES AND OPPORTUNITIES

As outlined, soft robotics offers interesting challenges and opportunities for progress in control theory. The problem of controlling soft robots is complex enough to stimulate research and wide enough to offer diverse perspectives and diverse approaches to explore. Control theory scientists can greatly contribute to the field, both by deepening the theoretical questions involved, and by integrating learning-based components into control systems. The progress of learning-based soft robot control still needs fundamental achievements. Among them, the field is lacking studies on motion planning and its closely related problem of shape planning and control, on the intractability of learning-based control in higher-dimensional continuous dynamical systems, on impedance control and feedback control, especially with intrinsic sensors. Table I shows some relevant state-of-the-art articles and their straightforward extensions. The next few sub-sections list research problems that are unique to the field of soft robotics and that are yet to be investigated in depth, either using learning-based techniques or model-based approaches. For each of the problems listed, we outline the challenges for learning-based methods.

A. *The dynamics of the soft body is strongly coupled to the environment*

One of the inherent challenges of soft robot control lies in the fact that dynamics of soft deformable structures are strongly dependent on the environment. When soft actuators generate forces, for example, the reaction forces are transmitted throughout the soft deformable structures all the way to the contact surfaces to the environment. Conversely, the forces imposed from the environment could also give various influences to the deformation of soft robot structures, which make it difficult to estimate the system own states as well as the consequence of actuation.

Many soft robots make use of soft-rigid hybrid body structures, that is not all of the body structures are composed of the materials with the same stiffness, but stiffness is deliberately varied across body structure in heterogeneous ways [53]. On the one hand, such anisotropic stiffness profiles are essential for producing directionality in deformation, which facilitate motion control problem. For example every soft pneumatic actuators are made of combined softer chamber attached to more stiff structures such that the actuator can be stretched or bent in a certain direction.

The system-environment interactions of soft-body robots are highly diverse for these reasons. Postures and dynamics of soft body are always dependent on their environmental conditions, and motions of the robots are very different consequently. Such unique dynamics can be taken advantage of for the simplified robot motion control as exemplified by the muscle synergies [54] and the environmental conditioning [55], [53].

B. ~~*How to apply control theory fundamentals to soft robotics*~~

~~Model-based control of soft robots remains a real challenge, especially because it depends on the type of model. Quantitative and qualitative models are commonly used for modeling kinematics or dynamics of soft robots. Quantitative modeling of soft robots are also known as model-based method and consists of expressing mathematically the relationship between the causes and effects, by using kinematic and dynamic fundamental equations. Generally, they consider several assumptions which yield less accurate models (eg. constant curvature), with time consuming and mathematical intractable issues for inverse formulation of the models. Qualitative modeling of soft robots or learning-based methods consist in dividing the parameter space into several classes according to the robot configurations, and then determining by learning the mathematical relations between the effects (measures), and causes (control inputs). They generally suffer from the huge size of the learning data-sets according to the high number of DOFs. Thus, it is sometimes difficult to establish well-structured control laws based qualitative model. A hybrid modeling, which combines the advantages of quantitative and qualitative methods, for modeling and solving the soft robot equations. The main advantage of the hybrid approach is the ability to derive the learning data-sets directly from the mathematical model of the soft robot.~~

C. *Controllability and observability of soft robotic systems*

Controllability and observability are two important mathematical measures used for linear system analysis [56]. However, equivalent analytical tests for non-linear systems are not well developed [57]. There have been recent progress in data-driven approaches that have been used for linear systems [58] and nonlinear systems [59]. Such empirical metrics can help further understand the capabilities and limitations of a given soft bodied system.

D. *Feedback control with embedded sensors*

Feedback control with embedded sensors can ~~provide additional behavioral ranges to~~improve the control of soft robotic systems, in terms of accuracy and richness of motor behaviors. Although there have been considerable developments in soft sensing technologies and reasonable progress in their modelling, the development of closed-loop controllers with rich tactile information is scarce. One of the challenges here is the need for fast, accurate, and robust models of these sensors, with a higher emphasis on the speed of the model. Another challenge is the difficulty in learning and acquiring higher level skills and exploration strategies. Developments from traditional robotics have immense potential to be transferred to soft robotic technologies, especially considering the fact that soft bodies provide safer and smoother tactile interactions. Some of the relevant works that can be directly translated to soft robotic sensors include unsupervised acquisition of tactile skills [60], direct learning of control policies using tactile states [61], [62], dimensionality reduction techniques using autoencoders [63] and multi-modal fusion [64].

E. *Physics-based modelling in soft robotics*

A clear drawback of learning-based models is its inability to be parameterized to design and control variables making

Reference	Research Problem	Achievements	Challanges	Year
[37]	Adaptive kinematic controllers	Task space control with external disturbances	Extension to learning of redundant configurations and inclusion of trajectory planning	2017
[36]	Kinematic redundancy resolution with feedback control	Task space control including orientation with disturbance rejection	Extension to learning of redundant configurations and inclusion of trajectory planning	2017
[40]	Visual servoing with adaptive kinematic controllers	Task space control based on visual inputs	Extension to learning of redundant configurations and inclusion of trajectory planning	2019
[42]	Control-oriented quasi-static modelling	Tracking of open loop trajectories in the task space	Extension to high-dimensional system	2020
[43]	Adaptation to morphological changes	Tip position and orientation control of a growing robot	Inclusion of offline models for control	2021
[39]	Multi-objective force and position control	Task space control with stiffness optimization	Extension to continuous action space	2017
[45]	Task-space dynamic control	Tracking high dynamics trajectory in the task space	Inclusion of feedback for closed-loop control	2017
[46]	Task-space model predictive control	Model predictive control with a one degree of freedom soft robot	Extension to high-dimensional system	2018
[47]	Task-space dynamic control with feedback	Closed-loop dynamic control for point reaching tasks	Extension to tracking tasks	2019
[48]	Control-oriented modelling for MPC	MPC controller for low dynamics trajectory tracking	Extension to high dynamics tracking tasks	2020
[49]	Distributed RNNs for data efficiency	Real-time dynamic predictive model of a soft manipulator	Extension to high-dimensional systems	2021
[50]	Hybrid models for data efficiency	Model-based optimal control of a soft continuum joint	Extension to dynamical high-dimensional systems	2021
[51]	Ensemble reinforcement learning for data efficiency	Dynamical controller for point reaching tasks in soft arm	Extension to trajectory tracking tasks	2021
[44]	Dynamic control for locomotion	Policy generation of gaits with variation in environmental conditions	Extension to faithful simulation environment	2017
[52]	Feedback Control with embedded sensors	Robust grasping and identification of objects	Extension to high-dimensional feedback information	2019

TABLE I

RELEVANT STATE-OF-THE-ART LEARNING-BASED CONTROLLERS PRESENTING THEIR NOVELTY AND FUTURE SCOPE SORTED BASED ON KINEMATIC CONTROLLERS(RED), MULTI-OBJECTIVE CONTROLLERS(YELLOW), DYNAMICS CONTROLLERS(GREEN), AND CONTROLLERS BASED ON EMBEDDED SENSORS(BLUE).

them unsuitable for design and control optimization. Recent developments in integrating physics-based modeling ~~W~~with ~~machine learning~~ML techniques could be a potential solution to alleviate this drawback [65], [66], [67]. The main idea behind these approaches is to use real-world data with ~~machine learning~~ML tools to generate governing dynamical equations. This can lead to explainable and parameterizable data-driven models that can also be faster to train. Such models can also lead to better theoretical understanding of complex soft robotic systems that are otherwise very difficult to analytically model. A recent example of such a method using Koopman operator theory for a soft robotic system can be found in reference [48] and using first principle models can be found in [50].

F. Transferability and adaptation of learned controllers

A future direction of research when it comes to learned soft robotic controllers is the problem of efficient transfer of learned models across 'similar' robotic systems. Along similar lines, the question of adaptation of learned controllers to changes in the body structure, either due to damages or intentional rearrangement is of relevance. Recent developments in generative adversarial networks seem to be promising in this direction [68], [69]. Although, most of the these works are limited to visual tasks [70], there have been recent attempts to uses GANs for transferring knowledge from simulated systems to real-world cases [71].

G. Benchmarking of learned-controllers

Benchmarking is an important tool in robotics research. It provides a method to quantitatively analyze different approaches that are developed with the same objective in mind [72], [73], [74]. It is difficult to develop benchmarking tasks for soft robotic devices and technologies due to large variety of problems that each techology is trying to address. Competition tasks can act as a general benchmarking task that allows us to evaluate an integrated system [75]. Benchmarking control algorithms is, however, easier and be done on simulated soft robotic models. As such there is an increasing need to develop benchmarking simulation platforms to evalaute learning-based control strategies in soft robotic devices and this can go a long way in accelerating the state of the current research landscape.

VII. CONCLUSIONS

The field of soft robotics and ~~machine learning~~ML has had rapid advancements in the last few decades. Soft robotics on one hand uses complex physical systems to solve hard physical problems, while ~~machine learning~~ML uses complex mathematical structures to solve hard computational problems. In tandem, they provide numerous advantages and capabilities, as evident in the recent achievements in the field. Owing to their relatively high damping, intrinsic safety, attractor dynamics and partial observability, ~~machine learning~~ML techniques are particularly well-suited for soft robotic systems. Relatively high damping, intrinsic safety and the dense attractor dynamics makes real-world exploration and sampling easier to obtain and learn. This is one of the key drawbacks of rigid robots, where damages to the system and chaotic dynamics reduces the applicability of ML techniques. Data-driven approaches are more accommodating to increasing complexity and non-linearity in the system, a trend that the field of soft robotics is driving towards, particularly with the concept of morphological computation. Yet, there are still numerous challenges and opportunities in this budding field that requires an interdisciplinary solution. Note that there are tasks where a simple open-loop controller would suffice (eg. [76], [77]) and we should strive to design our soft robots to this aim, if possible.

Primary challenges in the field include expanding the horizon of control problems from traditional end-effector control to more general shape control, impedance and stiffness control. This introduces sub-problems like motion planning, sensor placement, state estimation, etc. that have been very well studied in the literature. Further down the line, the more complex problem of design optimization and the coupling between the body dynamics and environment is to be addressed as we look towards more application-oriented research. A large body of control theory fundamentals like stability and robustness analysis, controllability and observability of soft systems are yet to deeply studied in the field. Data-driven methods can in fact be applied to do so and could help bridge the gap between theory and practise. Another interesting challenge in the field is the modelling of sensors itself, which is usually a simple linear calibration phase in traditional systems. Feedback control with these embedded soft sensors is a large topic with immense commercial applications. Finally, in order to make ML techniques more accessible and tractable for real-world applications, we need to look into physically explainable models and transferable models, which has the potential to reduce learning time and stability of learning. Throughout all these topics we can see that traditional modelling techniques, control architectures and control fundamentals can and need to be incorporated into existing learning modules for novel advancements in the field.

VIII. Sidebars

~~1. Soft Robotics~~

~~Soft robots are built with soft materials, with low Young's modulus, or with materials that are not soft per se, but are arranged in highly deformable geometries. Soft robots exist today over a wide range of morphologies (arms, fingers, legs, fins, ...), scales (from few mm to few m), abilities (reaching, grasping, walking, morphing, growing, swimming, jumping, crawling, digging, ...) and intended applications (in the biomedical field, underwater, in industry, ...). For the sake of clarity, we may focus here on the common case of soft robot arms, despite our description is intended to be completely general. Soft robot actuators have to deform the soft body, often in a continuum way. Similarly, sensors for soft robots are distributed in the soft structure and detect deformations induced by external forces, as well as those generated by robot actuators. Smart materials are used in soft robotics, like EAPs and SMAs, as well as fluidic actuation and other custom technologies. Soft robots are deformed by external forces, and this is designed to help their intended movements, according to the embodied intelligence paradigm, by which adaptive behavior emerges from the physical interaction of the body with the environment. Control is delegated in part to the physical body, that performs morphological computation [2]. In other words, a very short control loop is closed at the mechanical level, on the motor system, through a mechanical feedback. Building robots that can accept such mechanical feedback from the environment is the main motivation for soft robotics. Control is simplified in terms of computation and number of control variables [1].~~

2. Learning methods in soft robot control

Learning-based methods involve the empirical approximation of an unknown model of the soft robot that is embedded in the control solution. This process usually relies on the use of neural networks, but recently also deep neural networks or other data-driven approaches (e.g. Gaussian models) have been proposed. Figure 6 shows the learning approaches used for the control of soft robots, considering the ~~three~~ main learning classes.~~: supervised learning, unsupervised learning and reinforcement learning.~~

Supervised learning uses labeled datasets to train algorithms for classifying data or predicting outcomes accurately through regression. Collected data compose the training set, that is divided in input for the model and desired output. As input data are given to the supervised method, it adjusts its weights based on the desired output until the model to classify/predict has been fitted appropriately, which occurs as part of a cross validation process [78]. Supervised learning is used in soft robotics for learning different types of models including inverse kinematics or forward/inverse dynamics of soft manipulators. These models are then embedded in controllers.

In unsupervised learning, the algorithm is not provided with any label for the training data. As a result, unsupervised learning algorithms find occurring patterns in that training data set. ~~Common examples include clustering, where the algorithm automatically groups its training examples into categories with similar features, and principal component analysis, where the algorithm finds ways to compress the training dataset by identifying the features that allow to discriminate between different training examples.~~ ~~The only application in soft robot control based on unsupervised learning is object recognition for grasping.~~ So far, the only application of unsupervised learning is for object recognition [52], but it has not used for control.

Reinforcement Learning consists in a procedure where the agent performs an action, at each state, receiving ~~an assessment in a form of a~~ rewards from the environment. The agent derive the effectiveness of the state-action pairs until a policy is learned. [79] This process involves two steps: exploration ~~that refers to the possible ways it can use to accomplish the task~~ that refers to visiting unknown states or taking actions not taken yet and exploitation, which ~~is the process of using~~ relies on the previously gained ~~available~~ information ~~gained~~ to receive a large reward at a given state. ~~Robotics tasks can be seen as a Markov Decision Process that includes: a set of states, a set of actions, transition dynamics, a set of rewards and a discount factor, where the information about the environment are retrieved by sensors [80]. It should be noticed that, such information can be partial, requiring to dynamically store/learn previous information (by using for example recurrent neural networks).~~ Reinforcement Learning tasks can be classified into model-based and model-free approaches and on-policy and off-policy approaches. On-policy algorithms evaluate and improve the same policy which is being used to select actions. This means that the policy used for generating the behaviour and interacting with the environment is the one that it is trying to learn. In off-policy algorithms, these two policies are different ~~. For example, in Q-learning algorithm the agent learns~~

~~optimal policy by relying on a greedy policy and behaves using policies of other agents~~ [79]. In model-based learning, the agent exploits a previously learned model to make predictions about the task, whereas in model-free learning, the agent simply relies on some trial-and-error experience for action selection. Reinforcement learning is used in soft robotics to learn dynamic and kinematic models and, it can be used to directly learn the controller.

3. Bioinspiration

Bioinspiration is the extraction of principles, from the observation of living beings, to adopt in building human-made products. Soft robotics is deeply grounded in bioinspiration. We may say it is bioinspired per se, as most animals are soft fully (if they are small or live underwater or underground) or partly (if they have to compensate gravity). ~~Bioinspiration is not just copying living organisms but extracting the principles of interest for engineering, robotics, or other fields.~~ Embodied intelligence is one of the~~m~~ principles that we can learn from nature and motivates the need for compliant bodies, soft tissue and deformable structures in robotics. ~~A new wide range of soft robots inspired by animals and plants has risen at a rapid pace in the last 10 years. These artifacts are inspired from boneless biological organisms such as octopuses, elephant trunks or plant roots, which are able to exploit the mechanically intelligent arrangement to exhibit dexterous advanced capabilities in cluttered environments. This has been translated into robots made up of soft materials, with the aim of replicating the ability to undergo a large deformation under normal operation.~~ The underlying idea is that motor behaviour is not only controlled by computation, but emerges in part from the interaction of the physical body with the environment. Soft robots undergoing large deformations under external interactions can ~~to~~use principles of embodied intelligence and morphological computation to ~~exploit the soft material properties to enable machines with properties such as inherent compliance, variable stiffness, and highly dexterous~~achieve effective motion in unstructured environments. Control strategies applied on these artifacts try to exploit the aforementioned body properties to exploit morphological computation and simplify complex tasks.

4. State estimation in Soft Robotics:

State estimation in soft robotics is a challenging field; firstly because of the abstract definition of the state-space and secondly forthe developing nature of sensing technologies. Amongst them, embedded soft sensors are appearing that can be used~~important emerging tools~~ for proprioception, for exteroception and for developing feedback controllers [81], [18]. However, there are key challenges in modelling these sensors, as nonlinear time variant dynamic systems, which is further aggravated by intrinsic variability~~'s~~ introduced by the fabrication process [82]. Hence, learning-based approaches have been ubiquitously preferred for modelling soft sensory systems [83], [84], [85]. However, so far, these works have been limited to the development of task independent low-level models and not yet been applied for feedback control. This can be achieved by the use of a higher level controller over the learned lower level models or by directly learning an end-to-end controller.

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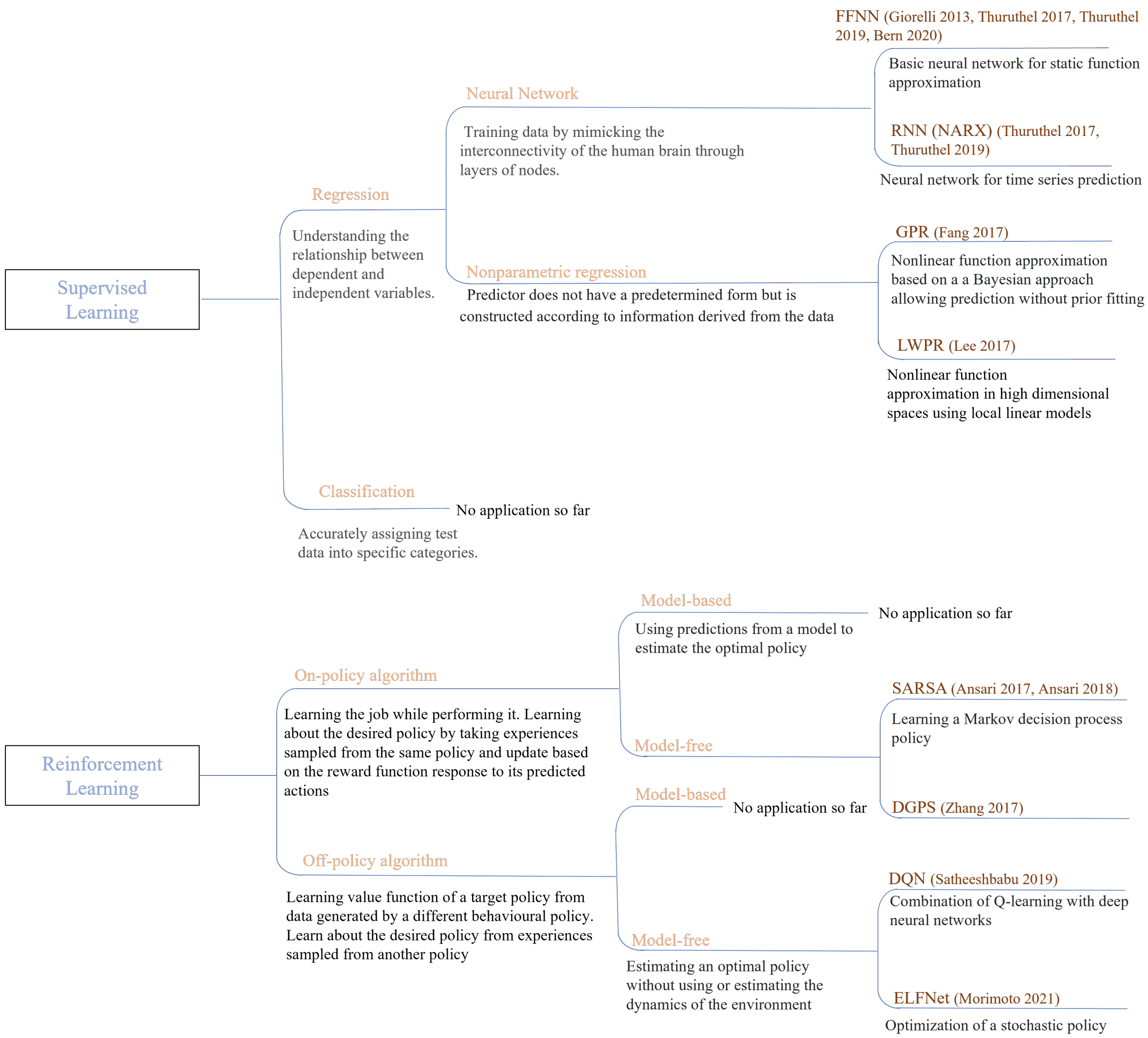

Fig. 6. Learning models used for the control of soft robots

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