A Brief Survey on the Role of Dimensionality Reduction in Manipulation Learning and Control

Fanny Ficuciello[1], *Senior Member, IEEE*, Pietro Falco[2], *Member, IEEE* and Sylvain Calinon[3], *Member, IEEE*

Abstract—Bio-inspired designs are motivated by efficiency, adaptability and robustness of biological systems dynamic behaviors in complex environment. Despite progress in design, the lack of sensorimotor and learning capabilities is the main drawback of human-like manipulation systems. Dimensionality reduction has demonstrated in recent robotics research to solve problems that affect high degrees of freedom (DoFs) devices. In this paper, a survey on the role of dimensionality reduction in learning and control strategies is provided by discussing different techniques adopted for dimensionality reduction, as well as learning and control strategies built on subspaces of reduced dimension across different fully-actuated and underactuated anthropomorphic designs.

I. INTRODUCTION

PIONEER scientific works on the human functioning demonstrate that great simplification, for planning and control of articulated organs, comes from the adoption of coordinated movements using patterns of motion [1]. Dimensionality reduction is an effective method to obtain simplified models that represent the essential properties of robot kinematics and dynamics [2].

Biological systems are examined for their versatility in different contexts, from neuroscience to engineering systems and robotics. In particular, a biological system has a multimodal sensor apparatus that processes different variables in parallel and performs actions using an iterative feedback mechanism in a dynamic process. In the context of system biology and neuroscience, dimensionality reduction is a useful instrument to understand and analyze biological systems and functions across diverse scales, ranging from cells, e.g. in neural control, up to sensorimotor systems organization [3]. In addition, in complex biological sensorimotor system, dimensionality reduction represents the solution that the central nervous system adopts to manage high redundancy by using salient variables, which can be defined according to a synergistic organization [4].

Another interesting evidence is that bio-inspired actuation systems based on tendon-driven motion transmissions, compliant mechanism and distributed elasticity hold great capabilities of adapting to changing environments thanks to enhanced compliance and agility. The embodiment of biological systems presents energy-efficiency, robustness and great adaptability to the external environment [5]. This justifies the trend of robotics researchers in drawing inspiration from human and in general from biological systems for robot design and control. As a matter of fact, to learn from experience, physical interaction is important and smart design makes the difference. However, high degrees of freedom (DoFs) and compliance increase the complexity of modeling and controlling these devices. Therefore, a recent and growing trend in the robotics community concerns the adoption of dimensionality reduction techniques, including the concept of sensorimotor synergies [6], to tackle the control problem of devices with high number of DoFs. In particular, anthropomorphic robotic devices for upper-limb manipulation to serve and substitute humans should achieve comparable motor and learning skills. Thus, learning, control and design aspects should not be separated in the complex problem of robotic manipulation. This is even more important when considering physical interaction that holds an important role in learning new tasks through trial-and-error. In this context, sensorimotor synergies and, in general, dimensionality reduction are of great importance in the learning process [7].

Another important issue towards building autonomous systems is to consider hybrid approaches between model-based control techniques and data-driven learning processes. Motion planning techniques that rely on analytical approaches require complex time-consuming processes such as object modeling, grasping affordance evaluation and accurate task description. A novel approach with respect to classical planning and control techniques is given by the integration in model-based strategies of manipulation activities learned/inspired by humans and real-time learning from actions strategies. Reinforcement learning (RL), based on exploration and trial-and-error, is the way humans adapt to changing environments. It is an essential component toward autonomous and intelligent robots [8], [9]. Dimensionality reduction can help in building efficient learning algorithms by developing policy search methods in a space of reduced dimensions that ensures fast convergence.

II. DIMENSIONALITY REDUCTION IN LEARNING

In the context of robot learning, the role of dimensionality reduction is tightly linked to the notion of movement primitives or skill primitives, which aim at representing complex and/or high-dimensional behaviors in a compact and adaptive form, by keeping only the essential features of the movement or behaviors to transfer to the robot. Movement/skill

primitives can be viewed as building blocks—adaptive bricks of movements—that can be (re-)organized in parallel and in series to create complex behaviors. The representations that have been proposed arise from different perspectives, including trajectory distributions, subspace clustering or regression. They differ in regard to the spread of the regions in which each model component is valid, from very local behaviors, with simple policies changing frequently, to global behaviors, with complex policies changing only sporadically. Despite many names have been introduced, connections can often be drawn between these different techniques. Fig. 1 presents an overview of these approaches.

Locally weighted regression (LWR)

LWR is an extension of the weighted least squares formulation in which K weighted regressions are performed on the same dataset. It aims at splitting a nonlinear problem so that it can be solved locally by linear regression. LWR was introduced by [10] and popularized by [11] in robotics. LWR often relies on *radial basis functions* (RBFs) acting as activation functions (receptive fields), with centers set to uniformly cover the input space, and a variance shared by all basis functions, selected to have a sufficient overlap for the retrieval of smooth trajectories. Multiple variants of the above formulation exist, including online estimation with a recursive formulation [12], or Bayesian treatments of LWR [13]. Fig. 1-*(a)* illustrates the use of LWR. LWR can be extended to *locally weighted projection regression* (LWPR) [14], by exploiting partial least squares to cope with redundant or irrelevant inputs, with an online algorithm to estimate the model parameters incrementally without having to keep the data in memory.

Applications of LWR and LWPR in robotics are diverse, ranging from whole-body inverse dynamics modeling [14] to skillful bimanual control such as devil-stick juggling [15].

Dynamical movement primitives (DMP)

DMP is a popular representation of movement primitives, derived from LWR. Originally presented in [16], the model has evolved through years with different variants and notations; see [17] for a review. At the core of DMP lies a controller in acceleration modulating a spring-damper system with nonlinear forcing terms represented by LWR. The acceleration command is composed of an attractor to an end-point with a predefined spring-damper system. At the beginning of the movement, the nonlinear forcing terms are prevalent and determine the shape of the movement. They then progressively disappear and let the spring-damper system drive entirely the behavior of the system to converge to a desired attractor point.

In standard DMP, the RBFs are predetermined as in LWR. The organization of the RBFs can alternatively be learned, by either considering the learning of each receptive field separately [17] or globally [18]. Fig. 1-*(a)* illustrates the principles of DMP.

Applications include the adaptive control of both discrete (point-to-point) and periodic (rhythmic) motions, with tasks such as reaching while avoiding obstacles [17], interactive
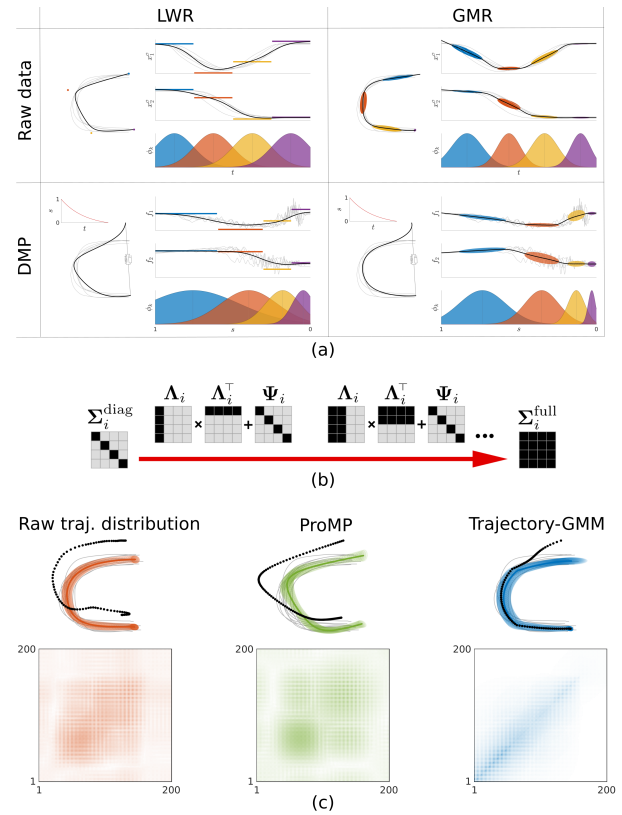

Fig. 1. Overview of various dimensionality reduction techniques used to represent movement in a compact and adaptive manner. (a) Use of LWR or GMR to learn a raw or DMP representation of movements. In the DMP representation, a forcing term profile is learned instead of the raw data. GMR allows the reorganization of the basis functions and models variation and coordination when full covariances matrices are employed. (b) Reduction of dimensionality by adding structures to the covariances, showing a gradual complexity from diagonal covariances to full covariances. (c) Retrieval of movements with various sparse representations of trajectory distributions. The retrieval (in black) is constrained to start at an initial position shifted from the original demonstrations, in order to show the effect of Gaussian conditioning on the different representations. The top graphs show the average path and spatial covariances. The bottom graphs show the covariance structures of the trajectory distributions, with the color of each entry proportional to its absolute value. With 10 demonstrations, a raw trajectory distribution will typically overfit the data and thus requires strong priors on the minimal allowed covariance to provide stable reproductions. We can see that the initial offset modifies the entire movement, highlighting the effect of the full covariance structure. The covariance of ProMP has a similar but sparser representation through the use of RBFs. Trajectory-GMM (GMM with dynamic features) is characterized by a band-structured covariance which has the effect of smoothly pulling back the movement toward the average of the trajectory distribution.

rehabilitation exercises in stroke-patients [16], playing the drums [19], or cleaning a whiteboard [20].

Gaussian mixture regression (GMR)

GMR is another popular representation for movement primitives, which can be used alone or in conjunction with DMP [21], [22]. It relies on linear transformation and conditioning properties of multivariate normal distributions. GMR provides a synthesis mechanism to compute output distributions in an online manner, with a computation time independent of the number of datapoints used to train the model. A characteristic of GMR is that it does not model the regression function directly. Instead, it first models the joint probability density

of the data in the form of a Gaussian mixture model (GMM). It can then compute very efficiently the regression function from the learned joint density model. In GMR, both input and output variables can be multidimensional. Any subset of input-output dimensions can be selected, which can change, if required, at each iteration during reproduction. This can be exploited to handle different sources of missing data, where expectations on the remaining dimensions can be computed as a multivariate normal distribution. Fig. 1-*(a)* illustrates the use of GMR.

GMR has been applied to learn various tasks, including collaborative transport of objects [23], pouring beverages in a glass [24], tactile correction of humanoid upper-body gestures [25], cooking rice [26] or rolling out pizza dough [22].

Gaussian process regression (GPR)

When learning movements and skills, we often have little or no prior knowledge about the specific model to use, but we still have some domain-specific knowledge that we would like to express in a more convenient form. For example, we may know that our observations are samples from an underlying process that is smooth, that has typical amplitude, or that the variations in the function take place over known time scales (e.g., within a typical dynamic range). Gaussian processes can be used as a way of reflecting various forms of prior knowledge about the physical process under investigation [27], [28].

In GPR, each observation in a dataset can be imagined as a datapoint sampled from a multivariate Gaussian distribution. The infinite joint distribution over all possible variables is then equivalent to a distribution over a function space. The underlying model requires hyperparameters to be inferred, but these hyperparameters govern characteristics that are quite generic, such as the scale of a distribution, rather than acting explicitly on the structure or functional form of the signals.

Various applications of GPR have been proposed for robot learning and control. In [29], GPR is exploited in a humanoid tracking and reaching movement, in which a set of external task parameters is associated with DMP parameters encoding movements, and where new task parameters are used to generate movements with GPR in an online manner. In [30], a sparse GP model is developed for the control of a PR2 robot, with an efficient online selection of the training points to learn inverse dynamics models from large datasets.

Trajectory distributions

Other approaches consider the encoding of movements as trajectory distributions expressed in a compact form. Fig. 1-*(c)* presents several techniques used as sparse representations of trajectory distributions. The most basic form consists of encoding a collection of M trajectories in a probabilistic form, by reorganizing each trajectory composed of T datapoints of dimension D as a hyperdimensional datapoint $\boldsymbol{\xi}_m = [\boldsymbol{x}_1^\top, \boldsymbol{x}_2^\top, \ldots, \boldsymbol{x}_T^\top]^\top \in \mathbb{R}^{DT}$, and fitting a Gaussian $\mathcal{N}(\boldsymbol{\mu}^{\boldsymbol{\xi}}, \boldsymbol{\Sigma}^{\boldsymbol{\xi}})$ to these datapoints. Since the dimension DT might be much larger than the number of datapoints M, additional structures, dimensionality reduction or priors are typically required. For

example, an eigendecomposition can be used to estimate only the first few eigencomponents.

Representing a collection of trajectories in the form of a multivariate distribution has several advantages. With such representation, new trajectories can be stochastically generated, and the conditional probability property can be exploited to generate trajectories passing through via-points (including starting and/or ending points). This is achieved by specifying as inputs the datapoints the system needs to pass through (with corresponding dimensions in the hyperdimensional vector), and by retrieving as output the remaining parts of the trajectory (in the form of a conditional distribution).

Probabilistic movement primitives (ProMP)

By using the same set of RBFs as for LWR and DMP, the ProMP (probabilistic movement primitive) model [31] assumes that each demonstrated trajectory $m \in \{1, \ldots, M\}$ can be approximated by a weighted sum of K normalized RBFs. By reorganizing the activation functions in a matrix $\boldsymbol{\Psi}$, the trajectories are represented in a subspace of reduced dimensionality by considering $\boldsymbol{\xi}_m = \boldsymbol{\Psi} \boldsymbol{w}_m + \boldsymbol{\epsilon}$, with $\boldsymbol{\epsilon} \sim \mathcal{N}(\boldsymbol{0}, \lambda \boldsymbol{I})$. A trajectory distribution can then be retrieved as a Gaussian $\boldsymbol{\xi} \sim \mathcal{N}\left(\boldsymbol{\Psi} \boldsymbol{\mu}^{\boldsymbol{w}}, \boldsymbol{\Psi} \boldsymbol{\Sigma}^{\boldsymbol{w}} \boldsymbol{\Psi}^\top + \lambda \boldsymbol{I}\right)$. With such structure, a Gaussian of DK dimensions is estimated (instead of the DT dimensions that one would require in the naive approach), providing a compact representation of the movement, by separating the temporal components $\boldsymbol{\Psi}$ and spatial components $\mathcal{N}(\boldsymbol{\mu}^{\boldsymbol{w}}, \boldsymbol{\Sigma}^{\boldsymbol{w}})$.

As for LWR and DMP, the parameters of the RBFs are usually predefined by the experimenter, with equally spread centers and a constant variance. Similarly to DMP, ProMP can be coupled with GMR to automatically estimate the positioning and spread of the basis functions as a joint distribution problem.

ProMP has been demonstrated in varied tasks such as table tennis strokes [32], playing the maracas or handling a hockey stick [31], as well as for collaborative object handover and assistance in box assembly [33].

Trajectory-GMM

An older technique, originating from the field of speech processing [34], consists of exploiting statistics from static and dynamic features of a trajectory, for the purpose of generating data. Sometimes called trajectory-GMM, and often employed in the context of *hidden Markov models* (HMM), it provides a simple approach to synthesize trajectories without discontinuities even when a small number of Gaussians is used to encode the movement. This is achieved by coordinating the distributions of both static and dynamic features in the time series. For the encoding of movements, velocity and acceleration can be used as dynamic features [35]. By reorganizing the position trajectory as a hyperdimensional datapoint $\boldsymbol{x}$, a state space trajectory comprising position, velocity and acceleration can be concatenated as a hyperdimensional datapoint $\boldsymbol{\zeta}$, computed with $\boldsymbol{\zeta} = \boldsymbol{\Phi} \boldsymbol{x}$ through the use of a large sparse matrix $\boldsymbol{\Phi}$ computing velocities and accelerations from consecutive positions.

In this approach, a GMM or HMM is used to model the dataset $\{\boldsymbol{\zeta}_1, \boldsymbol{\zeta}_2, \ldots, \boldsymbol{\zeta}_N\}$. During reproduction, a sequence of states $\boldsymbol{s} = \{s_1, s_2, \ldots, s_T\}$ of T time steps is first generated by the model. The likelihood of a movement $\boldsymbol{\zeta} = \boldsymbol{\Phi x}$ is given by $\mathcal{P}(\boldsymbol{\zeta}|\boldsymbol{s}) = \prod_{t=1}^{T} \mathcal{N}(\boldsymbol{\zeta}_t \,|\, \boldsymbol{\mu}_{s_t}, \boldsymbol{\Sigma}_{s_t})$, where $\boldsymbol{\mu}_{s_t}$ and $\boldsymbol{\Sigma}_{s_t}$ are the center and covariance of state s_t at time step t. This product can be rewritten in a matrix form as $\mathcal{P}(\boldsymbol{\Phi x}|\boldsymbol{s}) = \mathcal{N}(\boldsymbol{\Phi x} \,|\, \boldsymbol{\mu}_s, \boldsymbol{\Sigma}_s)$, with $\boldsymbol{\mu}_s$ and $\boldsymbol{\Sigma}_s$ a vector and matrix concatenation of the corresponding elements. By using the relation $\boldsymbol{\zeta} = \boldsymbol{\Phi x}$, a trajectory can then be retrieved by solving $\hat{\boldsymbol{x}} = \arg\max_{\boldsymbol{x}} \log \mathcal{P}(\boldsymbol{\Phi x} \,|\, \boldsymbol{s})$, resulting in a trajectory distribution $\boldsymbol{x} \sim \mathcal{N}(\hat{\boldsymbol{x}}, \hat{\boldsymbol{\Sigma}}^{\boldsymbol{x}})$ with parameters

$$\hat{\boldsymbol{x}} = \left(\boldsymbol{\Phi}^{\top} \boldsymbol{\Sigma}_s^{-1} \boldsymbol{\Phi}\right)^{-1} \boldsymbol{\Phi}^{\top} \boldsymbol{\Sigma}_s^{-1} \boldsymbol{\mu}_s, \quad \hat{\boldsymbol{\Sigma}}^{\boldsymbol{x}} \propto \left(\boldsymbol{\Phi}^{\top} \boldsymbol{\Sigma}_s^{-1} \boldsymbol{\Phi}\right)^{-1}.$$

Such trajectory distribution encoding with dynamic features has been exploited in robotics for human-like motion planning and control [36], [35], [37].

Subspace clustering

The representations presented in the above can be expressed as Gaussian mixture models. In the case of LWR, DMP and ProMP, the data are augmented with a phase or time variable, with activation functions that can be represented in the GMM as a fixed marginal distribution uncorrelated with the other dimensions. GMR then corresponds to the standard use of regression with RBFs. For high dimensional data, predefining the parameters of the GMM with this structure has the advantage that it avoids overfitting, at the expense of requiring more Gaussians than if the joint distribution would be estimated by a procedure such as *expectation-maximization* (EM) [35]. Indeed, classical Gaussian mixture models tend to perform poorly in high-dimensional spaces if too few datapoints are available. Namely, if the training set is $\{\boldsymbol{\xi}_n\}_{n=1}^{N}$ with $\boldsymbol{\xi}_n \in \mathbb{R}^D$, problems can occur if the dimension of the data D is too large compared to the size of the training set N. In particular, the problem can affect the estimation of full covariances $\boldsymbol{\Sigma}_k \in \mathbb{R}^{D \times D}$ in a GMM, because the number of parameters to be estimated quadratically grows with D.

Bouveyron and Brunet reviewed various ways of viewing the problem of coping with high-dimensional data in clustering problems [38]. In practice, three viewpoints can be considered: 1) Since D is too large compared to N, a global dimensionality reduction should be applied as a pre-processing step to reduce D; 2) Since D is too large compared to N, the solution space contains many poor local optima, and the solution space should be smoothed by introducing ridge or lasso regularization in the estimation of the covariance (avoiding numerical problem and singular solutions when inverting the covariances); 3) Since D is too large compared to N, the model is probably over-parametrized, and a more parsimonious model should be used (thus estimating a fewer number of parameters).

One example falling in the last category would be to consider spherical or diagonal covariances instead of full matrices, corresponding to a separate treatment of each variable. Although commonly employed in robotics, such decoupling is a limiting factor to encode gestures and sensorimotor streams, because it does not fully exploit principles underlying coordination, synergies and actionperception couplings [39], [40], [41].

Diagonal constraints are often too strongly constrained for motor skill encoding, because it loses important synergistic information among the variables. There are, however, a wide range of alternatives in mixture modeling, which are in-between the encoding of diagonal and full covariances, and that can readily be exploited in robot skills acquisition. These alternatives are typically studied as a subspace clustering problem that aims at grouping the data such that they can be locally projected onto a subspace of reduced dimensionality, thus helping the analysis of the local trend of the movement, while reducing the number of parameters to be estimated, and "locking" the most important synergies to cope with perturbations. Many possible constraints can be considered, grouped in families such as parsimonious GMM [38], *mixtures of factor analyzers* (MFA) [42] or *mixtures of probabilistic principal component analyzers* (MPPCA) [43]. For each approach, a dedicated EM update can be derived corresponding to the type of constraints considered [44], all reconstructing estimates of the full covariances in a GMM.

The representation of a movement or skill as a GMM is fully compatible with the above subspace clustering techniques. For example, the aim of *factor analysis* (FA) is to reduce the dimensionality of the data while keeping the observed covariance structure; see [45] for an example of application in robotics. A *mixture of factor analyzers* (MFA) assumes for each component i a covariance structure of the form $\boldsymbol{\Sigma}_k = \boldsymbol{\Lambda}_k \boldsymbol{\Lambda}_k^{\top} + \boldsymbol{\Psi}_k$, where $\boldsymbol{\Lambda}_k \in \mathbb{R}^{D \times d}$, known as the *factor loadings matrix*, typically has $d < D$ (providing a parsimonious representation of the data), and a diagonal noise matrix $\boldsymbol{\Psi}_k$. Fig. 1-*(b)* depicts this decomposition.

The factor loading and noise terms of the covariance matrix can be constrained in different ways (e.g., such as being shared across Gaussian components), yielding a collection of eight parsimonious covariance structures [44]. For example, MPPCA is a special case of MFA with the distribution of the errors assumed to be isotropic with $\boldsymbol{\Psi}_k = \boldsymbol{I}\sigma_k^2$.

Similarly to parsimonious GMM based on eigendecomposition, the covariances in MFA can be constrained by fixing d or by sharing elements among the mixture components. This encoding strategy can further be extended to variants of MFA aiming at optimizing the sharing and re-use of subspaces among the Gaussian components, such as in semi-tied covariance [46]. These techniques can be exploited to extend the concept of synergies to a wide range of motor skills, by simultaneously segmenting the movement and building a dictionary of synergies, allowing the re-use of previously discovered synergies; see [47] for an application in robotics.

III. DIMENSIONALITY REDUCTION IN PLANNING AND CONTROL

In planning and control, dimensionality reduction techniques are used to reduce the dimension of the grasp synthesis problem and to simplify motion generation for manipulation activities, as well as to reduce the number of control signals for fully actuated and underactuated anthropomorphic devices.

More recently, it has also been used to observe and classify manipulation and full-body actions.

Dimensionality reduction and postural synergies

In robotic manipulation, dimensionality reduction for control has been mainly used for anthropomorphic hands. An important pioneering work, in robotics and neuroscience, about dimensionality reduction in human hands is presented in [48]. The authors for the first time analyze the correlations between the finger joints of human hands while the subjects imagine to grasp different objects, and they called such correlations "postural synergies". Afterwards, different methods to map the postural synergies or "principal motions" from the human hand to anthropomorphic hands have been proposed [49], [50].

In robotics, the most common tool for deriving hand synergies is *principal component analysis* (PCA). Nonlinear approaches, such as Isomap, BP-Isomap and GPLVM, have also been explored. In [51], [52], nonlinear methods are used for embedding synergies. In [53] a *Gaussian Process Latent Variable Model* (GPLVM) is used to model the subspace of human hand motions, demonstrating better performance in reconstructing spatial and temporal grasping actions with respect to PCA and Isomap. A comparison between linear and nonlinear synergies can be found in [54].

Control of Grasping and Manipulation

In the field of control theory, only few papers exploited dimensionality reduction to simplify the control architecture. Thus, computed principal motions are then used to derive comprehensive planning and control algorithms that produce stable grasps for a number of different robot hand models [55]. In [56] an impedance controller is proposed for the DLR Hand II based on the synergy space [57], [58]. The authors found out that with only two synergies, 74% of the objects included into the DLR Hand II grasping database were successfully grasped. Besides the DLR Hand II, synergies have been applied to different robotic hands. In [59], [60], [61], postural synergies are evaluated for planning and control on the DEXMART hand, UB hand IV and Schunk hand.

Several works have also investigated synergies for manipulation in cyclic tasks. In [62] a dimensionality reduction for manipulation tasks based on the *unsupervised kernel regression* (UKR) method is applied to the problem of turning a bottle cap. In [63], the trend about sinusoidal of the synergies coefficients and the dependence of the sinusoidal wave from the orientation of the palm with respect to the bottle is highlighted. In [59], synergies learnt by humans are also used for a simple in-hand manipulation task.

The connection between motion synergies and haptic synergies is investigated in [64], where the relationship between the dimension of controllable internal forces and the number of synergy control inputs is studied. In particular, the concept of soft synergies, providing for compliance during the interaction with the object and the environment, has been introduced in [65] and exploited for robotic hands control [66] and design [67]. Furthermore, the use of synergistic motions is a very promising approach to control not only anthropomorphic

hands but more generally high DoF devices. Recently, research on muscular and postural synergies of the human hand [1], [68] has been extended to the whole upper limb apparatus [69] and to the whole body [2]. In [70], [71], the attitude of humans toward the use of combination of motion patterns to simplify planning and control of high DoF systems has been studied. A general method for systematically obtaining simplified models of humanoid robots is presented in [72], the problem of feature space dimensionality reduction for whole-body human motion recognition is addressed in [73].

Dimensionality Reduction for Planning

In robotic systems, planning the motion in complex, partially unstructured environments is a key issue for the success of tasks assigned to the robot [74]. With complex environments and robotic systems with many degrees of freedom, the dimension of the search space can become very large and the time for computing a suitable motion to fulfill the task becomes unreasonable for practical applications. A way to support planning is given by machine learning techniques, such as imitation learning and reinforcement learning, which are described in Sec. II. The research community started exploiting techniques based on synergies to reduce the dimensionality, not only for control problems, but also to reduce the state space dimension in planning problems [75], [76], [77]. The work in [75] presents a motion planning approach that exploits the concept of synergies (correlations) between degrees of freedom, with an extension to the velocity space. The approach has been recently extended in [77], in which task-dependent synergies are exploited. Such works demonstrate how synergies are suitable to plan the motion of arm-hand systems more effectively than with standard sample-based techniques. It is worth noticing that despite simplification, the use of a subspace of reduced dimension to plan and control motions leads to loss of information contained in higher order synergies that give critical details for both static grasp, when the hand adapts to the object shape, and for grasp preshaping [78]. Indeed, as pointed out in [4], the high dimension of biological sensorimotor systems provides dexterity and adaptability during interaction, while hierarchical synergies organization serves to optimize their use by selecting salient variables according to the task. In order to replicate these skills, robots should be provided with a similar functioning organization. It goes without saying that few synergies can fulfill grasping task, while fine manipulation needs higher level synergies to leverage additional degrees of actuation depending on task complexity, as described in [77]. How humans learn novel synergies and how task requirements shape synergies remain open problems to be addressed [79].

Dimensionality reduction for design and human observation

Based on the studies of synergies, low-cost hands, compliant and underactuated, are becoming increasingly popular in the robotics community [80], [81], [82], [67]. On one side, those hands can simplify grasping and potentially in-hand manipulation. On the other side, planning with high precision the behavior of hand-object systems becomes more difficult with standard planning approaches. For this reason, machine

learning is playing an increasingly important role in robotic grasping and manipulation in presence of compliance and underactuation.

Besides the applications in control, motion coordination and dimensionality reduction have been used to improve the observation of human grasping to improve the design of data gloves for human observation [83], for classification of human actions in manipulation [84] and full-body motion [85]. Recently, in the field of hand tracking with RGB cameras, the concept of dimensionality reduction is considered in the architectures of deep networks [86], [87]. These approaches usually take as input RGB images. In [87], for example, Oberweger *et al.* use a *convolution neural network* (CNN) part and a fully connected layer, which reduces the output of the CNN to a dimensionality smaller than the number of hand joints. They show that reducing the dimensionality can achieve better performance and can reduce overfitting.

As highlighted for planning and control, dimensionality reduction has pros and cons that also apply to underactuated mechanical designs; see e.g. [88]. Underactuation leads to a loss of dexterity and to a reduced robot workspace, thus the inverse kinematics problem does not necessarily have a closed-form solution [61]. This problem can be partially mitigated by introducing compliance in the mechanical design and by exploiting the interaction of the environment during task execution [79]. In general, the choice of the number of actuators of a robot is always a trade-off between design simplicity and dexterity.

IV. FUTURE PERSPECTIVES

The integration of learning techniques in control, as well as the combination of data-driven and model-based approaches, offer a solution to exploit robot experiences, by supplementing what the robot can measure through senses, and what is known a priori. The research on the topic is at a very early stage, some preliminary work are available in literature. In [89] a supervised learning strategy is used to plan the hand preshaping while a synergy-based control strategy is adopted to adjust the grasp for a final stable grasp according to the sensors feedback. An example of integration of data-driven with model-based approaches can be found in [90]. Here, a Grasp Quality Convolutional Neural Network (GQ-CNN) architecture that predicts grasp robustness from a point cloud is developed to reduce data collection time for deep learning of robust robotic grasp plans.

Despite the great research effort in grasping, manipulation, and hand-arm systems, the capability of current robotic systems is still not sufficient for real-word, highly-unstructured applications. In order to improve the performance of the approaches described in the previous sections, the research effort in the community can follow different, complementary directions towards an enhanced robustness of the current systems: multimodal perception, cross-modal perception, and data-efficient approaches to reduce the amount of training examples required. In particular, multimodal perception aims at improving the robustness of robotic perception by combining information from different types of sensors [91], [92], [93],

i.e. the training and test sets are constituted by multimodal data. A promising example consists of combining visual and tactile data. Cross-modal perception, on the other hand, consists in acquiring knowledge with a sensing modality and in reusing such a knowledge with a different modality [94]. For example, the robot can acquire knowledge from visual data and exploit the acquired knowledge when using tactile perception (cross-modal visuo-tactile perception), i.e. the training set is constituted by visual data and the test set by tactile data. Cross-modal perception is still quite unexplored while different works are available in literature concerning data efficient learning approaches. In [95] and [96], data-driven models are built to reduce the number of real-world interactions during reinforcement learning procedures. In [97] and [98], analytical models are leveraged and only the residuals are learnt in a data-driven fashion. In [99], Gaussian processes are used to model the cost function instead of modeling the dynamical model. A strategy based on learning-control synergy is used in [100] for learning by avoiding, during the process, irreversible events such as object slipping or collisions.

V. CONCLUSIONS

This short survey presented several research agendas exploiting dimensionality reduction in learning, planning and control strategies. We presented the biological motivation in terms of adaptability and robustness, some of the mathematical techniques and models used in robotics, as well as the varied applications that can benefit from such dimensionality reduction and encoding of synergies. We then discussed future perspectives and questions that remain open in these different fields.

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