ARTICLE IN PRESS
PLREV:746

Available online at www.sciencedirect.com

ScienceDirect

Physics of Life Reviews ••• (••••) •••–•••

PHYSICS of LIFE reviews

www.elsevier.com/locate/plrev

Comment

Transferring synergies from neuroscience to robotics ☆ Comment on "Hand synergies: Integration of robotics and neuroscience for understanding the control of biological and artificial hands" by M. Santello et al.

Oliver Brock [a,*], Francisco Valero-Cuevas [b]

[a] *Robotics and Biology Laboratory, Technische Universität Berlin, 10587 Berlin, Germany*
[b] *Department of Biomedical Engineering & Division of Biokinesiology and Physical Therapy, University of Southern California, Los Angeles, CA 90089, USA*

Received 9 May 2016; accepted 10 May 2016

Communicated by L. Perlovsky

Keywords: Neuroscience; Robotics; Synergies; Hand; Grasping

1. Introduction

Our understanding of how organisms control their limbs, i.e. systems with multiple muscles and joints, has had a profound and transformative impact on grasping and manipulation in robotics. Roboticists have struggled for a long time (and still do) with the algorithmic complexities that arise from the combinatorial explosion associated with the similarly high-dimensional problem of controlling robotic limbs. In the context of hands, this means that there are many muscular and kinematic degrees of freedom that need to be controlled to produce a desired manipulation behavior. Generating such control commands is provably difficult (e.g., as per the curse of dimensionality) even for very simple systems [6]. It is therefore critical to understand how organisms produce physical behavior using their complex anatomical limbs.

A compact characterization of relevant, low-dimensional control subspaces promises to greatly facilitate the replication of human manual capabilities in robotic hands. Several lines of research in neuroscience provided evidence that organisms indeed learn to identify and use such low-dimensional subspaces for neural control of limb motions and forces. Early work identified low-dimensional motor primitives in the spinal cord of vertebrates [17,18]. Other

DOI of original article: http://dx.doi.org/10.1016/j.plrev.2016.02.001.

☆ This work was supported by the Alexander von Humboldt foundation through an Alexander von Humboldt professorship (funded by the German Federal Ministry of Education and Research), the Soma project (European Commission, H2020-ICT-645599), and the German Research Foundation (DFG, BR 2248/3-1) to OB, and through grants from the National Institutes of Health R01AR050520 and R01AR052345 to FVC.

* Corresponding author.
E-mail addresses: oliver.brock@tu-berlin.de (O. Brock), valero@usc.edu (F. Valero-Cuevas).

http://dx.doi.org/10.1016/j.plrev.2016.05.011

work discovered a low-dimensional organization of human movements [10,16,23,33]. These experimental descriptions of dimensionality reduction of behavioral variables require only few basis functions, called synergies, that can be combined to explain the majority of the observed data.

But the last few decades have also seen heated debates about the nature of synergies. We say concepts in the plural because there are multiple definitions and interpretations of synergies. In the particular case of the neural control of limb and hand function, it remains debatable whether or not the nervous system implements synergies for the purpose of simplifying the dimensionality of the control problem [1,24,25,37,38]. Moreover, we have challenged the concept of muscle redundancy itself—which then challenges the need for simplification of the control problem and the need for synergies. The concept of muscle redundancy (having too many muscles or kinematic degrees of freedom) is indeed paradoxical with evolutionary biology and clinical reality. Why would an evolutionary process encode, grow, repair, control, etc., more muscles or joints than are strictly necessary? If the musculoskeletal system is redundant, why does disability arise even from mild neurological or orthopedic conditions? The fact that limbs are driven by musculotendons whose lengths are overdetermined (the rotation of a few joints sets the lengths and reflex responses of all muscles) also holds clues about this. This raises the possibility that organisms have evolved to have only enough degrees of freedom to be versatile while meeting the multiple spatio-temporal constraints of behavior in the real world given the structure and capabilities of the neuromuscular system, as discussed in detail in [21,24,38].

2. Descriptive versus prescriptive synergies

The ongoing debates about synergies in the realm of neuroscience must not hamper roboticists in their efforts to transfer and exploit the associated concepts in their field. But the challenges to the practicing roboticist include the lack of absolute certainty inherent to the deductive nature of neuroscience research [39], and the breadth of the neuroscience literature. Thus there is need to bring these different fields together in a way that helps both sides [38]. To facilitate this transfer in the context of synergies, it is important to distinguish between two possible interpretations of the dimensionality reduction in behavior: synergies could either be *descriptive* or *prescriptive* [21,38].

The subspace (i.e., manifold) of feasible motor actions is defined by the combination of the mechanical capabilities of the limb, the abilities and strategies of the controller, and the constraints (i.e., requirements) defining the task. Any successful execution of a task must by definition inhabit that subspace. Conversely, it is obvious that a motor command generated randomly will only by rare coincidence accomplish a desired task because it would need to have the good luck of being part of that lower-dimensional manifold, which may or may not be linear. Moreover, adding more task constraints defines a more particular control strategy as it further reduces the dimensionality of the subspace of all possible control commands [21].

Descriptive synergies are derived from experimental data. They capture the observed lower-dimensional structure of the subspace of feasible motor actions for a given task. Therefore, if we analyze behavioral variables (e.g. EMGs, kinematic variables, etc.), it is to be expected that we will detect that, as a consequence of meeting the constraints of the task, those variables will inhabit a low-dimensional manifold that *describe* the successful executions of the tasks.

By contrast, a prescriptive synergy is implemented by the controller to produce the task. It is an inherent property of the control law, and the controller is only able to execute control commands obtained from the combination of available synergies. A good example of this is the successful use of dynamic movement primitives for complex behavior in robots [31].

It is difficult—if not impossible—for statistical inference and deductive reasoning to uniquely identify the strategy used by a hidden controller (be it biological or robotic). Witness for example the challenges facing model-based estimation, machine learning, and optimal control when identifying the cost functions used by organisms [39]. Descriptive synergies are easily observed in experimental research. But proving the existence of prescriptive synergies of neural origins is much more difficult [25,37]—although there continue to be some recent efforts in that direction [2,20].

When exploring the distinction between descriptive and prescriptive synergies, one must bear in mind data suggesting that the nervous system may not have absolute, independent control over all muscles because of both anatomical and neural constraints [32,40]. Importantly, the role of perception on motor control, and even independence of muscle actions, is an important one that also requires further understanding [1,3,4,17,21,22,26,29,30,35].

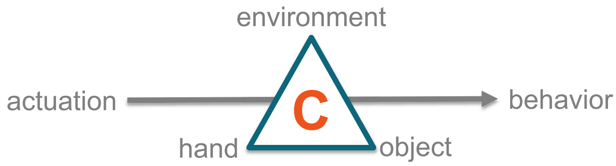

Fig. 1. Identical actuation signals can lead to different behaviors: Physical compliance (C) present in the hand, the object, and the environment. Compliant physical interactions between the hand, the object, and the environment (triangle) differentiate a single actuation command (left) into different behaviors (right).

3. What should roboticists copy?

Roboticists possess the luxury of being able to design and implement any prescriptive synergy they like—because they design and implement the controller and the hand. But, as we will see, they should still worry about the distinction between prescriptive and descriptive synergies.

Traditionally, roboticists have relied on robots in which every degree of freedom can be controlled independently. Synergies, by their very nature, limit the controller to a lower-dimensional manifold, leading to reduced controllability, functional limitations, and loss of generality and versatility.

The simplicity associated with prescriptive synergies has triggered what one might call a paradigm shift in robotic manipulation [31,34], as also described in the paper we comment upon here. Carefully designed controllers on suitably constructed hands naturally operate within a prescriptive, low-dimensional manifold, while still exhibiting highly competent behavior [8,11,13,15]. These results are compelling roboticists to develop novel computational tools [8,28] and under-actuated hands [5,8,11,13,27] to model and implement these synergies.

In synergy-based robotic systems, identical control commands can result in behavior that varies significantly. This variation arises from compliant interactions among the hand, environment, and object [11] (see Fig. 1). This is both a bug and a feature. A bug because it precludes repeatable function, but a feature because the intentional exploitation of compliance can lead to robust and dexterous behavior, such as in-hand manipulation [15]. Furthermore, the compliant interaction between hand, manipulandum, and the environment was shown to be an essential factor in human grasping performance [14,19]. Compliance thus seems invariably linked to the notion of robustness of synergies and competent hand behavior in the real world.

This discussion shows that compliance can differentiate the prescriptive synergies of the hand, leading to descriptive synergies of observed behavior. In other words, behavior is *generated* using prescriptive synergies, but the power of synergies arises when these prescriptive synergies are modulated in a task- and situation-specific way due to the mechanical interactions between hand, object, and environment.

How then should roboticists find the appropriate prescriptive synergies for a particular task? This is difficult as the observed behavior in humans (descriptive synergies) does not directly reveal the required control used by the nervous system (prescriptive neural synergies, if they indeed exist). Defining task-relevant prescriptive synergies is further complicated by the observation that their performance depends in important ways on the specific parameters and context of the task.

Recent, and unpublished, results based on experiments presented elsewhere [14,19], point to the possibility that both prescriptive and descriptive synergies observed in grasping behavior vary as a function of contact between the hand, the manipulandum, and its support surface. For example, the prescriptive synergies used to actuate the hand may differ when an object is grasped from a flat support surface, or when it is grasped while positioned against a wall. The invoked prescriptive synergies may also differ when an object is picked up for use, or picked up to be placed somewhere else. In these situations—even if the same prescriptive synergies were evoked—features in the environment will lead to the differentiation of prescriptive synergies into observed behavior. Roboticists refer to these features of the environment as environmental constraints [14]. These environmental constraints probably play an important role in the design of prescriptive synergies.

All of this might imply that, to fully understand the behavior of the human hand and to replicate it on robots, we have to consider all aspects of behavior at the same time, including the environment within which the behavior is performed. We must understand how to design prescriptive synergies tailored to a particular task. These prescriptive synergies, when modulated by compliance to object and task-relevant environmental constraints, should achieve the

Please cite this article in press as: Brock O, Valero-Cuevas F. Transferring synergies from neuroscience to robotics. Phys Life Rev (2016), http://dx.doi.org/10.1016/j.plrev.2016.05.011

desired task-specific behavior. And we must also understand how these prescriptive synergies can be generated by a combination of hand morphology and synergy-based control.

While we must consider all aspects of the task to design suitable descriptive synergies, we should probably not consider all tasks at the same time. It is unlikely that a single set of “universal” synergies will yield desirable behavior for all tasks and in all situations [36]. To identify useful synergies, therefore, it seems more fruitful to find use case categories, sharing relevant aspects of manipulandum, task, and environmental constraints. Only by finding prescriptive synergies tailored to a particular use case category can we be sure that the interaction between hand, object, and environment modulates the prescriptive synergy into the desired behavior. Such task-specific prescriptive synergies are then able to exhibit maximum robustness and versatility.

The endeavor of fully realizing synergy-driven manipulation in robotics will require that neuroscience and robotics come together to find answers that are out of reach for the each of the disciplines alone. The distinctions between the deductive efforts in neuroscience and the synthetic efforts in robotics are diminishing. If we are careful to take into consideration the different languages, approaches, and goals of these different fields then, what is one of the most fundamental aspects of human intelligence—the use of our hands—, may prove to be a fertile ground for the merging of these two scientific approaches and disciplines.

Appendix A. Terminology

The notion of synergy has been defined in many different ways in the context of neuroscience. Importing these concepts into robotics risks even greater confusion. We would therefore like to make our understanding of synergies explicit so that readers may determine where our notions differs from theirs.

Underlying the following discussion is the assumption that synergies represent an approximation to a lower-dimensional subspace (or manifold) that contains data recorded from a higher-dimensional space. One can make various assumptions about the structure of the lower-dimensional manifold and these assumptions will determine the computational tool one brings to bear to extract the approximation of the manifold from data. In most basic cases, the computational tool is PCA and we restrict our discussion to this case. The area of (nonlinear) dimensionality reduction offers a broad set of alternatives [9].

Referring to Fig. 1: Let d_A be the dimensionality of the actuation space A. In a tendon-driven hand, for example, there might be d_A motor-driven tendons whose actuation can be combined to actuate the hand. The actuation commands, rather than coming from A directly, might be chosen from a lower-dimensional subspace $\underline{A}$, where the dimensionality of $\underline{A}$ is $d_{\underline{A}} < d_A$. For example, the first two tendons could always be actuated the same way, reducing the dimensionality of the actuation space to $d_A - 1$. The dimensionality d_A is determined by the mechanics, whereas $d_{\underline{A}}$ is determined by the control. In the case that $d_A = d_{\underline{A}}$, roboticists say that the hand is fully actuated.

Assuming that $d_{\underline{A}} < d_A$, the lower-dimensional actuation space $\underline{A}$ can be obtained from a set of executed actuation commands a_i by a principal component analysis (PCA). The $d_{\underline{A}}$ principle components are called *prescriptive* synergies. They form a basis for the actuation patters of the hand. The elements of this basis are combined linearly to actuate the hand. These synergies are called prescriptive, because—once they are fixed—they define and limit the set of all possible actuation patterns to $\underline{A} \subset A$, prescribing a certain behavior of the hand.

We can make the same arguments for the behavioral space. Assume a hand has $d_B = 20$ movable joints. The space of all possible hand behaviors, B, therefore has d_B dimensions. The observed behavior of the hand may again lie in a lower-dimensional subspace, $\underline{B}$, with $d_{\underline{B}} < d_B$. It is even very likely that the observed behavior lies in such a subspace, as the observed behavior must comply with the constraints imposed by the tasks from which the behavior resulted.

From the observed behavior, we can determine the $d_{\underline{B}}$ synergies by performing a PCA on experimental data. These synergies, by construction, span the observed space $\underline{B}$. They are called *descriptive* synergies, as they describe the observed behavior of the hand. This behavior is the result of actuation commands (prescriptive synergies), possibly modulated by the compliant interactions between hand, object, and environment (see Fig. 1). If, for example, $d_A < d_B$, roboticists would call the hand “under-actuated.”

In summary, both prescriptive and descriptive synergies simply approximate the lower dimensional-manifold containing the observed data (actuation data and behavior data, respectively). Prescriptive synergies approximate the data on the left side of Fig. 1 and descriptive synergies the data on the right side.

Please cite this article in press as: Brock O, Valero-Cuevas F. Transferring synergies from neuroscience to robotics. Phys Life Rev (2016), http://dx.doi.org/10.1016/j.plrev.2016.05.011

The authors of the review we are commenting on have developed robotic notions of synergies [8]. These synergies describe a formalism to simulate and predict the resulting behavior caused by a particular actuation signal. These "robotic synergies" have resulted from the import of descriptive synergies from neuroscience into robotics: Santello et al. extracted descriptive synergies from human grasping data [16]. These synergies were imported into robotics by designing hands that mechanically encode one or several of these synergies [7,8,12]. In other words, the prescriptive synergies and the corresponding mechanical design of the hands were chosen such that the resulting behavior matched the descriptive synergies observed in humans.

Three types of synergies have been introduced, each relying in principle on the same prescriptive synergies to produce behavior [8]. They vary in what aspects of the triangle in Fig. 1 they consider in their prediction of behavior. *Geometric synergies* predict the hand's behavior from an actuation signal under the assumption that no other interaction takes place: the triangle in Fig. 1 does not exist and only the mechanical properties of the hand are simulated. *Soft synergies* include interactions between the hand and the object. The simulation computes the contact forces between hand and object based on the difference between the geometric-synergy-behavior of the hand and the soft-synergy behavior, which prevents the hand from penetrating the simulated object (as a result of considering hand/object interactions). Soft synergies have been further extended into *adaptive synergies* [8], where the contact forces of the soft synergies are balanced, leading to an adaptation of the hand's shape and contact forces to the grasped object. All of these synergies rely on a model of the hand and possibly an object to determine the behavior expected from an actuation signal. Soft and adaptive synergies can also be used to control the behavior of hands by varying a parameter to form linear variations of the actuation signal.

In our understanding, these three types of robotic synergies represent and implement three specific mappings from actuation to behavior, and are not a description of the space of actuations or behaviors alone, as are prescriptive and descriptive synergies. When discussing synergies at the intersection of neuroscience and robotics, we should therefore carefully differentiate the use of these concepts.

References

[1] Alessandro C, Delis I, Nori F, Panzeri S, Berret B. Muscle synergies in neuroscience and robotics: from input-space to task-space perspectives. Front Comput Neurosci 2013;7.

[2] Berger DJ, Gentner R, Edmunds T, Pai DK, d'Avella A. Differences in adaptation rates after virtual surgeries provide direct evidence for modularity. J Neurosci 2013;33(30):12384–94.

[3] Bizzi E, Cheung VCK. The neural origin of muscle synergies. Front Comput Neurosci 2013;7.

[4] Bizzi E, Mussa-Ivaldi FA, Giszter S. Computations underlying the execution of movement: a biological perspective. Science 1991;253(5017):287–91.

[5] Brown E, Rodenberg N, Amend J, Mozeika A, Steltz E, Zakin MR, et al. Universal robotic gripper based on the jamming of granular material. Proc Natl Acad Sci 2010;107(44):18809–14.

[6] Canny J. The complexity of robot motion planning. MIT press; 1988.

[7] Catalano MG, Grioli G, Serio A, Farnioli E, Piazza C, Bicchi A. Adaptive synergies for a humanoid hand. In: Proceedings of teh IEEE-RAS international conference on humanoid robots. 2012.

[8] Catalano MG, Grioli G, Farnioli E, Serio A, Piazza C, Bicchi A. Adaptive synergies for the design and control of the Pisa/IIT SoftHand. Int J Robot Res 2014;33(5):768–82.

[9] Clewley RH, Guckenheimer JM, Valero-Cuevas FJ. Estimating effective degrees of freedom in motor systems. IEEE Trans Biomed Eng 2008;55:430–42.

[10] Collins DR, Turvey MT. A stochastic analysis of superposed rhythmic synergies. Hum Mov Sci 1997;16(1):33–80.

[11] Deimel R, Brock O. A novel type of compliant and underactuated robotic hand for dexterous grasping. Int J Robot Res 2016;35(1–3):161–85.

[12] Della Santina C, Grioli G, Catalano M, Brando A, Bicchi A. Dexterity augmentation on a synergistic hand: the Pisa/IIT SoftHand+. In: Proceedings of the IEEE-RAS international conference on humanoid robots. 2015.

[13] Dollar AM, Howe RD. The highly adaptive SDM hand: design and performance evaluation. Int J Robot Res 2010;29(5):585–97.

[14] Eppner C, Deimel R, Álvarez-Ruiz J, Maertens M, Brock O. Exploitation of environmental constraints in human and robotic grasping. Int J Robot Res 2015;34(7):1021–38.

[15] Fass T. In-hand manipulation with the RBO hand 2. https://www.youtube.com/watch?v=-RdwLMCD8G4, 2016.

[16] Flanagan S, Flanders M, Soeching JF. Postural hand synergies for tool use. J Neurosci 1998;18(23):10105–15.

[17] Giszter SF. Motor primitives—new data and future questions. Curr Opin Neurobiol 2015;33:156–65.

[18] Grillner S. Control of locomotion in bipeds, tetrapods, and fish. Compr Physiol 2011.

[19] Heinemann F, Puhlmann S, Eppner C, Álvarez-Ruiz J, Maertens M, Brock O. A taxonomy of human grasping behavior suitable for transfer to robotic hands. In: Proceedings of the IEEE international conference on robotics and automation. 2015. p. 4286–91.

[20] Hongchul Sohn M, Ting LH. Suboptimal muscle synergy activation patterns generalize their motor function across postures. Front Comput Neurosci 2016;10(7).

[21] Inouye JM, Valero-Cuevas FJ. Muscle synergies heavily influence the neural control of arm endpoint stiffness and energy consumption. PLoS Comput Biol 2016;12(2):e1004737.
[22] Kang N, Cauraugh JH. Bimanual force variability in chronic stroke: with and without visual information. Neurosci Lett 2015;587:41–5.
[23] Kelso SJA. Dynamic patterns: the self-organization of brain and behavior. MIT Press; 1997.
[24] Kutch JJ, Valero-Cuevas FJ. Muscle redundancy does not imply robustness to muscle dysfunction. J Biomech 2011;44(7):1264–70.
[25] Kutch JJ, Valero-Cuevas FJ. Challenges and new approaches to proving the existence of muscle synergies of neural origin. PLoS Comput Biol 2012;8(5):e1002434.
[26] Mechsner F, Kerzel D, Knoblich G, Prinz W. Perceptual basis of bimanual coordination. Nature 2001;414(6859):69–73.
[27] Odhner LU, Jentoft LP, Claffee MR, Corson N, Tenzer Y, Ma RR, et al. A compliant, underactuated hand for robust manipulation. Int J Robot Res 2014;33(5):736–52.
[28] Prattichizzo D, Malvezzi M, Gabiccini M, Bicchi A. On motion and force controllability of precision grasps with hands actuated by soft synergies. IEEE Trans Robot 2013;29(6):1440–56.
[29] Rácz K, Valero-Cuevas FJ. Spatio-temporal analysis reveals active control of both task-relevant and task-irrelevant variables. Front Comput Neurosci 2013;7:155.
[30] Ren J, Huang S, Zhang J, Zhu Q, Wilson AD, Snapp-Childs W, et al. The 50s cliff: a decline in perceptuo-motor learning, not a deficit in visual motion perception. PLoS ONE 2015;10(4).
[31] Schaal S, Peters J, Nakanishi J, Ijspeert A. Learning movement primitives. In: Robotics research. The eleventh international symposium. Springer; 2005. p. 561–72.
[32] Schieber MH, Santello M. Hand function: peripheral and central constraints on performance. J Appl Physiol 2004;96(6):2293–300.
[33] Scholz JP, Schöner G. The uncontrolled manifold concept: identifying control variables for a functional task. Exp Brain Res 1999;126:289–306.
[34] Soft Manipulation, European project funded under the Horizon 2020 program: http://www.soma-project.eu, 2016.
[35] Ting LH, Macpherson JM. A limited set of muscle synergies for force control during a postural task. J Neurophysiol 2005;93(1):609–13.
[36] Todorov E, Ghahramani Z. Analysis of the synergies underlying complex hand manipulation. In: Proceedings of the annual international conference of the IEEE EMBS. 2004.
[37] Tresch MC, Jarc A. The case for and against muscle synergies. Curr Opin Neurobiol 2009;19(6):601–7.
[38] Valero-Cuevas FJ. Fundamentals of neuromechanics. Biosystems and biorobotics series, vol. 8. London: Springer-Verlag; 2015.
[39] Valero-Cuevas FJ, Hoffmann H, Kurse MU, Kutch JJ, Theodorou EA. Computational models for neuromuscular function. IEEE Rev Biomed Eng 2009;2:110–35.
[40] van Duinen H, Gandevia SC. Constraints for control of the human hand. J Physiol 2011;589(23):5583–93.