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Comment on “Hand synergies: Integration of robotics and neuroscience for understanding the control of biological and artificial hands” by M. Santello et al

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Control of the human hand has been both difficult to understand scientifically and difficult to emulate technologically. The article by Santello and colleagues in the current issue of *Physics of Life Reviews* [1] highlights the accelerating pace of interaction between the neuroscience of controlling body movement and the engineering of robotic hands that can be used either autonomously or as part of a motor neuroprosthesis, an artificial body part that moves under control from a human subject's own nervous system. Motor neuroprostheses typically involve a brain-computer interface (BCI) that takes signals from the subject's nervous system or muscles, interprets those signals through a decoding algorithm, and then applies the resulting output to control the artificial device.

For most of the 20th century, the digits of the human hand were viewed as mechanically independent effectors that the brain controlled individually. Although some robotic hands were created with independent digits, the complexities of actuating and controlling such hands required sacrificing much of the natural dexterity characteristic of biological hands. Consequently, in practice both the prosthetic hands available to human amputees and the hands of industrial robots were simple grippers.

Late in the 20th century scientific understanding of the hand began to change. Fingers do not move with complete independence, muscles do not act simply on one finger at a time, and movements of different fingers are not mapped into distinct territories of the cerebral motor cortex [2]. Mathematical techniques for extracting frequent patterns of covariation in high-dimensional spaces were applied to the joints of the hand (principal component analysis, [3]) and to the electrical activation of muscles (non-negative matrix factorization, [4]), identifying commonly used patterns of covariation referred to as kinematic and muscular synergies, respectively. The extent to which the nervous system uses such synergies to simplify the computational problem of controlling the biological hand, and at what level of the nervous system—cerebral cortex, brain stem, spinal cord—such synergies might be instantiated, remains a matter of ongoing investigation [5-7].

Nevertheless, the concept of synergies already is being applied productively to robotic technology. Various groups working with different robotic hands are developing a variety of

synergy-based strategies. The “soft-hand” approach highlighted in [1] implements a robotic hand that enables the user to grasp a wide variety of objects with a single synergy that closes all the digits, the digits adjusting themselves to the object’s shape through a combination of mechanical and software compliance. In contrast, the hand of the comparatively “hard” modular prosthetic limb can be controlled with a small number of synergies, each of which produces a hand posture useful for grasping objects of a particular shape [8]. For neuroprosthetic applications, synergies reduce the cognitive burden of consciously controlling many degrees of freedom—joints or fingers—simultaneously.

In addition to the cognitive burden a neuroprosthesis puts on the subject’s mind, the complexity of controlling a biomimetic hand places a substantial computational load on the BCI. For real-world, practical application, computational load is a constraint: The computers needed to control a robotic hand cannot yet be packaged and powered in a mobile device one can readily wear to go to work or out shopping. As pointed out in [1], synergies can be implemented not only through software, but also in the mechanical design of a robotic hand itself, reducing the computational load. Indeed, in biological hands certain synergies are created mechanically by interconnections between tendons that go to adjacent fingers and by incomplete separation of muscle compartments acting on such tendons. In the most powerful finger flexor muscle, the *flexor digitorum profundus*, such biomechanical synergies facilitate simultaneous closure of the fingers around a large object, though the same features also make it difficult to flex the little finger toward the palm without flexing the ring finger as well [9]. Implementing some synergies mechanically in a robotic hand thus emulates the biological hand.

A major challenge for neuroprosthetics currently is to provide sensory feedback from robotic hands. Thousands of sensory receptors in the skin, muscles, and joints of the biological hand provide feedback on both the shape of the hand and the physical properties—e.g. texture, temperature and weight—of the object being handled. Given that the number of channels currently available for delivering feedback from a robotic hand to the nervous system is limited, extracting synergies that represent the most common patterns of biological feedback is a potentially useful strategy that deserves extensive exploration [1].

Whether mechanical or computational, synergies also have their own limitations. Synergies simplify control of frequently performed tasks, but if applied alone will fall short of achieving the most dexterous movements. Sophisticated uses of the human hand, such as playing a piano or tying a surgical knot, require highly individuated movements of the digits. But just as reconstructing 100% of the original data requires the same number of principle components as the number of original data dimensions, synergies cannot reproduce all the movements of which the biological hand is capable unless the number of synergies approaches the number of mechanical degrees of freedom in the biological hand and/or the number of muscles that move the biological hand. Of course, using so many synergies to control a robotic hand would render the dimensionality reduction afforded by synergies pointless. While synergies will be extremely useful for controlling a robotic hand in a large majority of common circumstances, more complex control will need to be superimposed to emulate the biological hand completely.

A primary motivation for applying neuroscientific understanding of the biological hand to improving robotic hands has been to create neuroprostheses that improve the lives of humans with amputations or neurological disease. But as described for the synergy concept in [1], various aspects of neuroprosthetics already are being used as tools to further scientific understanding of the nervous system in ways previously unimagined. When controlling a neuroprosthetic device, for example, the patterns of neural and/or muscular activity differ from those used to control the biological counterpart [10, 11]. Neuroscientists currently are examining the extent to which activity can deviate from the natural patterns employed in controlling movement of the biological arm and hand [12, 13]. To some extent, muscle or neural activity can control even an arbitrary BCI output, such as the motion of a cursor on a computer screen, in ways unrelated to the normal, biological function of those muscles or neurons [14-16]. Recently engineered to control prosthetic devices for patients, neuroprosthetics thus are being used to understand the basic neuroscience of brain flexibility and plasticity, which in turn will further accelerate the interplay between neuroscience and prosthetics engineering.

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References

1. Santello M, Bianchi M, Gabiccini M, Ricciardi E, Salvietti G, Prattichizzo D, et al. Hand synergies: Integration of robotics and neuroscience for understanding the control of biological and artificial hands. *Physics of Life Reviews*. 2016
2. Schieber, MH., Reilly, KT., Lang, CE. Motor cortex control of a complex peripheral apparatus: The neuromuscular evolution of individuated finger movements. In: Riehle, A., Vaadia, E., editors. *Motor Cortex in Voluntary Movements: A distributed system for distributed functions*. Boca Raton: CRC Press; 2005. p. 87-107.
3. Santello M, Flanders M, Soechting JF. Postural hand synergies for tool use. *J Neurosci*. 1998; 18:10105–15. [PubMed: 9822764]
4. D'Avella A, Saltiel P, Bizzi E. Combinations of muscle synergies in the construction of a natural motor behavior. *Nature Neuroscience*. 2003; 6:300–8. [PubMed: 12563264]
5. Roh J, Cheung VC, Bizzi E. Modules in the brain stem and spinal cord underlying motor behaviors. *J Neurophysiol*. 2011; 106:1363–78. [PubMed: 21653716]
6. Cheung VC, Piron L, Agostini M, Silvoni S, Turolla A, Bizzi E. Stability of muscle synergies for voluntary actions after cortical stroke in humans. *Proc Natl Acad Sci U S A*. 2009; 106:19563–8. [PubMed: 19880747]
7. Mollazadeh M, Aggarwal V, Thakor NV, Schieber MH. Principal components of hand kinematics and neurophysiological signals in motor cortex during reach to grasp movements. *J Neurophysiol*. 2014; 112:1857–70. [PubMed: 24990564]
8. Wodlinger B, Downey JE, Tyler-Kabara EC, Schwartz AB, Boninger ML, Collinger JL. Ten-dimensional anthropomorphic arm control in a human brain-machine interface: difficulties, solutions, and limitations. *J Neural Eng*. 2015; 12:016011. [PubMed: 25514320]
9. Reilly KT, Schieber MH. Incomplete functional subdivision of the human multitendoned finger muscle flexor digitorum profundus: An electromyographic study. *Journal of Neurophysiology*. 2003; 90:2560–70. [PubMed: 12815024]
10. Taylor DM, Tillery SI, Schwartz AB. Direct cortical control of 3D neuroprosthetic devices. *Science*. 2002; 296:1829–32. [PubMed: 12052948]

11. Ganguly K, Dimitrov DF, Wallis JD, Carmena JM. Reversible large-scale modification of cortical networks during neuroprosthetic control. *Nat Neurosci.* 2011; 14:662–7. [PubMed: 21499255]
12. Sadtler PT, Quick KM, Golub MD, Chase SM, Ryu SI, Tyler-Kabara EC, et al. Neural constraints on learning. *Nature.* 2014; 512:423–6. [PubMed: 25164754]
13. Jarosiewicz B, Chase SM, Fraser GW, Velliste M, Kass RE, Schwartz AB. Functional network reorganization during learning in a brain-computer interface paradigm. *Proc Natl Acad Sci USA.* 2008; 105:19486–91. [PubMed: 19047633]
14. Hochberg LR, Serruya MD, Friehs GM, Mukand JA, Saleh M, Caplan AH, et al. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature.* 2006; 442:164–71. [PubMed: 16838014]
15. Radhakrishnan SM, Baker SN, Jackson A. Learning a novel myoelectric-controlled interface task. *J Neurophysiol.* 2008; 100:2397–408. [PubMed: 18667540]
16. Law AJ, Rivlis G, Schieber MH. Rapid acquisition of novel interface control by small ensembles of arbitrarily selected primary motor cortex neurons. *J Neurophysiol.* 2014; 112:1528–48. [PubMed: 24920030]