

EDITORIAL | *Society for the Neural Control of Movement*

Highlights from the 29th Annual Meeting of the Society for the Neural Control of Movement

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INTRODUCTION

The Society for the Neural Control of Movement arrived for the first time in Asia for their 29th annual meeting in Toyama, Japan (from April 22–29th, 2019). The meeting attracted over 325 attendees with a broad range of expertise and interests. Two focused premeetings on the neurophysiology of eye and hand motor control took place in Kyoto and Tokyo, Japan, respectively. These small-format meetings fostered interactions and in-depth discussions. In addition, a satellite meeting focused on “predictive coding and active inference to know and explore the world” took place before the annual meeting. The main meeting’s topics ranged from neurophysiology (single and multiunit neural recordings, calcium imaging, fMRI) to computation (deep learning, computational modeling of neural circuits and behavior, and muscle modeling) and behavioral implications for movement control and learning. Altogether, the presented work covered a broad range of motor research across different model systems—from primate physiology, human psychophysics, and mouse motor skills to theoretical models of fruit fly biomechanics.

As has been done in previous years (Gallego et al. 2017a; Mazurek et al. 2018), here we present a brief summary of the highlights of the meeting. We categorized these highlights into four main themes: 1) circuits of sensory and motor control, 2) computational tools and models for motor neuroscience, 3) the relationship between muscle properties and motor control, and 4) naturalistic and complex behavioral tasks.

CIRCUITS OF SENSORY AND MOTOR CONTROL

Marking the 50th anniversary of Dr. David Marr’s seminal paper on the cerebellum (Marr 1969), the 29th Neural Control of Movement meeting naturally lent itself to a discussion of the legacy of the Marr-Albus-Ito theory (Albus 1971; Ito 2006). This discussion was especially poignant given that the society meeting was the first in Japan, the late Dr. Ito’s home country. Dr. Mackenzie Mathis started off the panel on the legacy of the Marr-Albus-Ito theory by highlighting the role of behavior in studying the cerebellum. It is well known that patients with

cerebellar degeneration have deficits adapting to force fields (Smith and Shadmehr 2005) and other visuomotor perturbations (Martin et al. 1996; Tseng et al. 2007). Mathis, using a novel force field adaptation paradigm in mice (Mathis et al. 2017), demonstrated that when she chemogenetically inactivated cerebellar Purkinje cells, the mice were not able to reliably adapt to the imposed force field. However, these mice also exhibited problems in control, i.e., they moved in an ataxic fashion (Mathis 2017). In contrast, when the somatosensory cortex was inactivated optogenetically, mice were similarly not able to adapt to the force field yet did not display any clear control problems (Mathis et al. 2017). This dissociation suggests a critical role for cortical motor areas in updating sensorimotor internal models. Dr. David Ostry presented an intriguing set of data from humans that was consistent with the aforementioned work on the somatosensory cortex in mice; Ostry showed that continuous theta-burst transcranial magnetic stimulation delivered to somatosensory cortex—but not motor cortex—appeared to impair the consolidation of motor memories over a 24-h period.

Dr. Megan Carey, using chemogenetics in mice, showed that the cerebellum is required for split-belt adaptation (Darmohray et al. 2019). This result is consistent with work on humans (Morton and Bastian 2006). Interestingly, and in contrast to the force field adaptation experiments involving reaching (Mathis et al. 2017), lesion experiments suggested that the cerebral cortex is not required for split-belt adaptation (Darmohray et al. 2019). Moreover, specific subcomponents of a single adaptation task (i.e., the spatial and temporal aspects of gait adaptation in split-belt tasks) appear to rely on dissociable neural circuits (Darmohray et al. 2019). Taken together, these recent studies in mice and humans highlight the complex nature of motor adaptation, and suggest that the different adaptation tasks (e.g., force field adaptation versus split-belt treadmill adaptation) may recruit distinct neural circuits.

According to the Marr-Albus-Ito theory, Purkinje cell complex spikes, which are driven by the climbing fibers of the inferior olivary nucleus, constitute the teaching signal for cerebellar learning. Dr. Kazuo Kitamura described how Purkinje neurons within aldolase C compartments, a marker for the longitudinal stripes within the cerebellum (Brochu et al. 1990), have highly synchronous complex spike activity both

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during spontaneous and (sensory) evoked behavior (Tsutsumi et al. 2015). Subsequently, he presented recordings of complex spike activity during an auditory discrimination and a forelimb lever-press task that also revealed high levels of synchrony. Dr. Mark Wagner also presented a poster with similar conclusions in a different reaching task in mice. In a distinct tracking task in primates, Dr. Martha Streng also showed that complex spike firing in the primate cerebellum appears to convey predominantly predictive information about the behavior for online control (e.g., upcoming position errors and kinematics) (Streng et al. 2017b). A cerebellar Purkinje cell also receives input from parallel fibers that modulate a high-frequency simple spike activity. Streng also highlighted the importance of the interactions between simple and complex spikes for motor control (Streng et al. 2017a).

Dr. Terence Sanger offered a bird's-eye view on the broader status of the Marr-Albus theory (Albus 1971; Marr 1969). This revolutionary theory on cerebellar learning has, for the most part, stood the test of time. However, as Sanger noted, it has required key modifications and still faces many unanswered questions—for instance, Sanger emphasized the crucial insight from Ito that the cerebellum can only be understood in the context of other brain areas via cerebrocerebellar communication loops (Ito 2006). Excitingly, modern imaging techniques now allow researchers to address questions about cerebrocerebellar coordination by simultaneously recording large populations of neurons across multiple regions of the brain and the nervous system. For example, Dr. Mark Wagner and colleagues performed chronic imaging in both the cerebral cortex and the cerebellum during a learning task. They revealed that initially dissimilar activity patterns of cells in layer 5 of the cortex and cells in the granular layer of the cerebellum converged onto low-dimensional, task-relevant representations as learning progressed (Wagner et al. 2019). Imaging also demonstrated that important behavioral variables, like reward expectations, are encoded in granular cells of the cerebellum (Wagner et al. 2017). Several presenters acknowledged the importance of studying cerebellar function in a variety of tasks (Darmohray et al. 2019; King et al. 2019; Wagner et al. 2017), and in conjunction with cerebral cortical activity (Wagner et al. 2019). Moving forward, both of these approaches will be critical for elucidating the functional heterogeneity of the cerebellar cortex in task domains beyond motor learning and control (Diedrichsen et al. 2019).

In an engaging and inspiring distinguished career award talk, Dr. John Kalaska presented a historical perspective of research investigating the role of cortex in voluntary movements. He revisited influential studies from 1960 to 1980, referring to this period as the “Golden Era.” Furthermore, he highlighted that in that period researchers 1) were restricted to neural recordings generally using single microelectrodes, 2) focused on reducing the degrees of freedom to single joint movements (flexion and extension), and 3) interpreted results in a transcortical servo-control loop model (Evarts 1968; Fetz and Cheney 1980; Thach 1978). These years were influential because studies seemed to provide the first supportive evidence for what might be encoded at the level of single neurons in the motor cortex, which included movement dynamics, muscle patterns, and kinematics (Georgopoulos et al. 1982; Kalaska and Crammond 1992; Sergio et al. 2005). Different areas like dorsolateral premotor cortex (PMd) and parietal Brodmann area 5 (A5)

were later also analyzed in this way (Crammond and Kalaska 1989; Hamel-Pâquet et al. 2006; Scott and Kalaska 1997; Scott et al. 1997).

Finally, Kalaska summarized how advances in research on cortical coding for movement has evolved, emphasizing 1) simultaneous multiunit neural recordings with dimensional reduction techniques (Churchland et al. 2012; Gallego et al. 2017b, 2018; Wagner et al. 2019), 2) expanding research to complex scenarios related to higher order planning, action selection and decision making (Cisek and Kalaska 2005; Kalaska and Crammond 1995; Wang et al. 2019), and 3) optimal-feedback and dynamical network models (Lillicrap and Scott 2013; Omrani et al. 2016; Pruszynski et al. 2011). Kalaska also emphasized that current dynamical systems views of the motor system should try to incorporate our rich knowledge of how neurons also appear to encode specific kinematic and dynamic variables.

The population-level dynamical systems analyses revealed that reaching movements are accompanied by rotational dynamics within primary motor cortex (M1) (Churchland et al. 2012). Dr. Sliman Bensmaia presented a poster to study the extent to which such dynamics are also present during grasping movements but failed to find strong signatures of rotational dynamics. This suggests that low-dimensional rotational dynamics might not be a universal task-invariant signature of M1 activity (Goodman et al. 2019). Dr. Brian Dekleva presented an analysis of neural population dynamics in tasks involving grasping and contrasted the relation between dynamics during reaching while grasping (transport of objects), which appeared to change depending on the task demands/constraints.

Flowing with the dynamical systems paradigm, Andrew Zimnik approached the question of whether and how motor cortical neurons generate movement sequences, training primates to generate a sequence of two reaching movements while recording from multiple neurons in the motor cortex. His data suggested that in M1 each movement is prepared and executed sequentially; preparation for the next movement began during the execution of the previous movement. Dr. Mark Churchland showed new results contrasting the neural population dynamics known from primary motor cortex (Churchland et al. 2012) with the neural dynamics in the supplementary motor area (SMA) in an hand-cycling task. He presented a distinct population geometry in SMA with low trajectory divergence and suggested that this result hints at the class of computations the SMA performs, such as guiding of future action (Russo et al. 2019). Finally, as mentioned in Dr. Kalaska's talk, beyond leveraging multiunit neuronal recordings while focusing on a variety of complexity related to motor control (planning, action selection, decision making), there is a need to develop computational models to make sense of these large scale neural/behavioral data.

COMPUTATIONAL TOOLS AND MODELS FOR MOTOR NEUROSCIENCE

One panel focused on novel methods based on Deep Learning. Deep Learning has made tremendous strides in recent years and has impacted many fields, from controlling robots, to optimizing computer vision tasks and improving generative modeling (Insafutdinov et al. 2017; Kingma and Welling 2014; Krizhevsky et al. 2012; Lillicrap et al. 2015). In the first talk of

this panel, Dr. Alexander Mathis highlighted how algorithms based on deep convolutional neural networks (Cao et al. 2017; Insaftudinov et al. 2017; Krizhevsky et al. 2012) can be harnessed for markerless pose estimation in the laboratory. He showed data from various behaviors and species, including: mice engaged in an odor-guided navigation task, reaching in mice, and estimating the pose of egg-laying fruit flies (Mathis et al. 2018) and also highlighted how these methods can be extended outside the laboratory, for instance, to track hunting cheetahs in 3D based on multiple cameras (Nath et al. 2019). He outlined how pose data can be utilized to compactly describe behavior, or to study biomechanics (e.g., of cheetah tails). DeepLabCut is already widely used and showed up in several talks and presentations throughout the meeting, e.g., by Drs. Kathleen Cullen and Alexander Gail (Berger and Gail 2018). In the second talk of this panel, Dr. Nidhi Seethapathi presented a study for using markerless pose estimation technology to study movement disorders in infants: They collected hundreds of videos from YouTube and had them hand-annotated on Mechanical Turk, a crowdsourcing platform (<https://www.mturk.com>). These training data were then used to fine-tune OpenPose (Cao et al. 2017) to extract the posture of infants from videos (Chambers et al. 2019). In summary, deep convolutional neural networks can efficiently extract behavior from video data across animal species (Mathis et al. 2018; Nath et al. 2019), as well as humans, with novel applications from sports science (Kaplan et al. 2019) to rehabilitation (Cronin et al. 2019).

Beyond processing videos, deep learning has also tremendously advanced the analysis of other forms of data. Determining the underlying structure for complex data sets, like the spiking patterns of neurons, is in general computationally intractable. Kingma and Welling (2014) developed efficient approximations that make it possible to learn tractable generative models of high-dimensional neural data. A recently published method, LFADS (latent factor analysis via dynamical systems) leverages these advances for learning models of spiking data (Pandarinath et al. 2018). LFADS attempts to reproduce spikes from populations of neurons using a generative model comprising recurrent neural networks. Remarkably, the learned low-dimensional dynamics of the recurrent network often describe behavioral or internal states (that are not used during training) extremely well (Pandarinath et al. 2018). Dr. Pandarinath also emphasized how LFADS can be used for systems that are not governed by autonomous dynamics, but driven by external variables, such as when modeling sensory areas. Fundamentally, LFADS's cost function is highly non-convex, and the fitting process is therefore nonunique and highly dependent on hyperparameters. Dr. Pandarinath described efforts to train these networks in the cloud while "evolving" the hyperparameters to address this issue. These techniques will greatly contribute to the robustness of LFADS in the future. In the final talk of the session, Dr. Laura Driscoll focused on studying Deep Networks as "model organisms" for understanding the brain. Feedforward, convolutional networks have become popular tools for understanding the ventral visual pathway (Yamins and DiCarlo 2016). Here, Driscoll focused on a recurrent neural network that was trained to solve multiple cognitive tasks, which have been studied in monkeys (Yang et al. 2019). Her analysis techniques could help elucidate under-

lying mechanisms of how the networks, and by extension, brains solve complex cognitive tasks.

In several talks throughout the conference, researchers addressed key theoretical questions in human motor learning and control. For example, a popular model are inverse and forward models for motor control (Wolpert and Kawato 1998), with the former helping to specify the motor commands needed to achieve a desired sensory outcome and the latter helping to predict the sensory consequences of an elicited motor command. Conventional theories of sensorimotor adaptation claim that adaptation relies on the updating of a forward model. Dr. Alkis Hadjiosif presented a provocative set of experiments suggesting that, contrary to the prevailing view, sensorimotor adaptation appears to reflect updating of an inverse model rather than a forward model. In standard human visuomotor rotation experiments, where both forward and inverse models predict similar adaptive behaviors, dissociating the two is difficult. Hadjiosif dissociated them by having subjects perform reaches under a "mirror reversal" condition. Hadjiosif argued that a forward model should be able to easily adapt to mirror reversals, as the sensory errors themselves reflect the model's output directly, and the controller can be adapted to reduce those errors. However, an inverse model must make assumptions about the motor-to-sensory-outcome relationship, e.g., that leftward adaptation should counteract a rightward sensory error. Such an assumption will fail for mirror reversals, causing a counterproductive inflation in visual error. Indeed, subjects' errors increased, with movements drifting away from targets along the mirror axis, supporting the predictions of inverse model-driven adaptation.

Another idea that comes from these models is that feedback responses to mechanical perturbations also rely on an internal model of arm dynamics (Kurtzer et al. 2008). Rodrigo Maeda presented a set of experiments showing that when human participants are trained for extended periods to generate elbow movements with shoulder fixation (altered arm dynamics), they learn to slowly reduce shoulder muscle activity. It is efficient to reduce shoulder muscle activity in this context because fixing the shoulder joint eliminates the effect of the interaction torques that arise at the shoulder joint with forearm rotation (Maeda et al. 2017) and removes the need to activate the shoulder muscles. This feedforward learning was found to transfer to feedback responses to mechanical perturbations that were never directly trained during the shoulder fixation, suggesting that feedforward and feedback control share an internal model of the arm's dynamics (Maeda et al. 2018).

Dr. Tomohiko Takei investigated the nature of these feedback responses in an optimal feedback control model and found that disruption of control policy variables impaired accuracy and response speed, while impairing state estimation affected only accuracy. He then used cooling techniques to deactivate various brain regions (Meyer-Lohmann et al. 1975) during experiments in which monkeys received mechanical perturbations applied to their upper limb. He found that when PMd was cooled, accuracy and response speed were both impaired, but when A5 was cooled, impairments were observed only for accuracy. He concluded that PMd and A5 offer distinct contributions to these feedback pathways, supporting control policy and state estimation, respectively. In addition, perturbing the forward model resulted in oscillatory movement, which is consistent with cooling the dentate nucleus

(Meyer-Lohmann et al. 1975). This work also nicely tied in with the careful perturbation and modeling analysis of motor adaptation in mice during reaching (Mathis et al. 2017) and locomotion (Darmohray et al. 2019) that we discussed under CIRCUITS OF SENSORY AND MOTOR CONTROL above.

THE RELATIONSHIP BETWEEN MUSCLE PROPERTIES AND MOTOR CONTROL

The last panel session of the conference focused on the muscular basis of motor control. Drs. Madhusudhan Venkadesan, Neville Hogan, Kiisa Nishikawa, and Lena Ting emphasized that the complex material properties of muscles are crucial features of motor control. While the speakers used diverse methodologies and model systems to investigate the relationship between muscles and behavior, all emphasized the need to more thoroughly understand the relationship between the material properties of muscles and behavior, as well as the need to incorporate nonlinear properties of muscles into muscle models.

Classical views of motor control suggest that neural commands from the brain specify task-level kinematic or dynamic parameters (e.g., end point velocity or joint torques, respectively). The speakers presented an approach to motor control where the material properties of the muscle, along with the muscle's recent history of movement and activation, are significant factors. One essential property is muscle stiffness, or the extent the muscle will lengthen in response to altered tension during muscle activation (Herbert 1988). Dr. Hogan explained that muscle stiffness, which increases with force, helps to keep the skeleton from collapsing. The increase in stiffness due to muscle activation must be faster than the destabilizing stiffness of the skeletal geometry to counteract the instability in the musculoskeletal system. Additionally, the coactivation of an antagonist muscle is used to modulate joint stiffness, ultimately helping to further stabilize joint posture (Hogan and Sternad 2013). Dr. Venkadesan provided a related viewpoint on the importance of muscle stiffness in relation to stability. He argued that muscles transition between fluid and solid states depending on the dynamics of movement. For example, when a finger joint buckles under pressure, the muscle transitions from a solidlike to a more fluid state as stiffness rapidly decreases.

Efforts to understand how muscle properties contribute to motor control are often limited by the complexity and realism of the computational models used to investigate force generation. Since the late 1950s, researchers have primarily used variants of the sliding filament/cross-bridge theory to model muscle contraction. Although models based on this theory successfully represent the force output from concentric and isometric contractions, such models do not include important properties that reflect an actively stretched muscle (Herzog et al. 2015). More specifically, these models cannot explain biomechanical nonlinearities such as the nonlinear increase in muscle force when motor neuron action potentials arrive in rapid succession (Srivastava et al. 2017) or after the stretching of a muscle (Sober et al. 2018). It is necessary to create models that accurately reflect muscle properties to fully understand biomechanics. Drs. Nishikawa and Ting discussed new advances in the sliding filament model that explain specific nonlinear properties in muscles.

Research in Dr. Nishikawa's laboratory has led her group to explore how titin, a muscle protein that connects the end of the thick filaments (myosin) to the Z-disk, might help to explain the nonlinear force output of muscles. Based on their experimental results, they hypothesize that the influx of calcium in response to muscle activation leads to the N2A region of titin binding to actin, causing titin to stiffen. Once titin is attached to actin, the cross bridges between actin and myosin act as rotors and wind titin around the thin filaments. This winding action stores energy in the PEVK region of titin, a repeated sequence containing a high quantity of proline amino acids. The two-step winding filament model has successfully simulated nonlinear force enhancement in response to stretching and nonlinear force depression in response to shortening (Nishikawa et al. 2012).

Dr. Ting presented human and animal experiments investigating the role of short-range stiffness in response to postural perturbations (De Groot et al. 2017) and how muscle spindles encode short-range stiffness in the muscle (Blum et al. 2017, 2019). Short-range stiffness of muscle, which is movement history dependent, causes muscle force to increase quickly and transiently in response to stretch. The increase of force induced by short-range stiffness can be measured by taking the first time derivative of the force, known informally as "yank." Data from single muscle fibers demonstrated that yank increases proportionally with the level of muscle activation and may explain forces in the silent period (the background activity) during balance perturbation. To accurately reflect joint kinematics and stability following perturbation, Dr. De Groot and colleagues created a model of short-range stiffness that can be used in conjunction with phenomenological muscle models used in musculoskeletal simulations (De Groot et al. 2017, 2018).

The data presented in this panel convincingly showed that intrinsic and biomechanical properties of muscles influence the effects of neural activity on behavior. Instead of assuming a simple role of a muscle as a linear force generator, the complex mechanical and material properties of a muscle impact the relationships between external forces, neural activity, and behavior. Because these muscle features contribute to the motor output, it is likely these features shape patterns of neural activity in the motor system by constraining the neural strategies the brain uses to learn and perform motor tasks.

NATURALISTIC AND COMPLEX BEHAVIORAL TASKS

Several exciting talks about human motor learning and control addressed fundamental conceptual issues and outlined new challenges. For instance, while most motor learning tasks are conducted with sitting subjects, in the real world we are often moving, whether by foot, bicycle, or car. How does body acceleration affect action selection and execution? Or, in the realm of sensorimotor adaptation, much work has pointed toward the adaptation of a forward model as the fundamental underlying mechanism—are there problems with these views? Many talks and posters raised similar important, challenging questions.

In the spirit of last year's emphasis to broaden our human motor learning techniques to incorporate more naturalistic tasks (Mazurek et al. 2018), several researchers discussed the important issue of the interaction between naturalistic whole-

body movements (real or simulated) on action selection, execution, and motor corrections. Dr. Shlomi Haar presented a novel effort to design and study real-world motor learning using the game of pool table billiards and showed a large scale data analysis to compare individual performance, rates of learning, and movement variability in this scenario (Haar et al. 2019). Dr. Carlos Hernandez-Castillo developed a handheld device that could simulate slip in any of the five fingers and used it to investigate the influence of somatosensory information on whole arm corrective responses. He found fast feedback responses in shoulder muscles that varied with slipping direction and magnitude and that were potentiated when combined with joint perturbations (Hernandez-Castillo et al. 2019). Dr. Sasha Reschechtko presented an experimental approach to study the integration of tactile information during reaching in an unconstrained reach/antireach task in three dimensions toward a physical target. By using wireless EMG electrodes and a very small magnetic tracking probe, he captured relevant muscle activations and kinematics without interfering with the free-reaching task. His results showed that corrections during reaches, guided by tactile feedback, had latencies similar to those guided by visual feedback (Pruszynski et al. 2016), while touch-guided corrections under an antireach instruction had less direction specificity and occurred at a similar latency.

Dr. Pieter Medendorp also addressed the topic of naturalistic movements by measuring how body acceleration signals affect action selection, specifically showing that saccadic decisions (where to look) are biased toward the direction of body acceleration and may be driven by cortical modulation driven by those acceleration signals. Dr. Andrea Green discussed how bipolar galvanic vestibular stimulation, which simulates head rotation, modulates reaching movement in a manner consistent with a transformation from a head-centered to a body-centered reference frame (Moreau-Debord et al. 2014). These results suggest that vestibular signals are directly incorporated in voluntary reach control computations.

A challenge for studying complex behavior is to develop ways to measure the associated neural correlates. Using an fMRI-compatible device, Dr. Atsushi Yokoi presented a novel behavioral paradigm in which participants were trained to produce distinct sequences of finger key presses while in the scanner. He found that motor cortex specifically represented individual finger movements, while premotor and parietal cortices showed a mixture of chunk, sequence, and finger transition representations (Yokoi and Diedrichsen 2019). Dr. Alexander Gail presented a wireless, multiarea, single unit-neural recording system that could be employed in non-human primates while they make simultaneous walking-and-reaching movements, opening new avenues for investigations of more naturalistic behaviors (Berger and Gail 2018).

Dr. Gelsy Torres-Oviedo was awarded with the early career award and presented her comprehensive body of work characterizing muscle activity pattern when human participants walked on a split-belt treadmill. She showed that muscle activity changes during split-belt walking reflect adapted sensorimotor internal models for gait control (Iturralde and Torres-Oviedo 2019). Moreover, adaptation of these new gait patterns becomes less flexible with age. Studying more naturalistic scenarios, such as walking, has an added value for understanding and developing rehabilitation approaches for a variety of patients with neurological injury. Torres-Oviedo also presented

data from stroke patients, in which cerebral lesions interfered with the execution, but not the recalibration of motor commands (de Kam et al. 2019).

Altogether, these presentations highlighted several advances in the field toward understanding naturalistic behavior. Key challenges discussed in the meeting can be summarized as 1) bringing more naturalistic behavioral scenarios to the laboratory settings requires developing ways to record and analyze large data sets, from motion tracking of the eyes to multiple body segments; 2) developing such complex tasks for neurophysiology recordings across model systems is still a challenge, but recent research has pushed the boundaries of tasks that can be used for these investigations; and 3) a key challenge to overcome is still generalization of findings across platforms. However, modern tools like LFADS (Pandarinath et al. 2018) and DeepLabCut (Mathis et al. 2018; Nath et al. 2019) can aid in the analysis of behavior and brain activity in complex naturalistic settings.

CONCLUSION

Taken together, advances highlighted in this 29th meeting of the Society for the Neural Control of Movement in Toyama, Japan approached movement control and learning from exciting perspectives. Studies that focused on recording at the cellular level showcased new analysis techniques and cutting-edge recording and imaging technologies to simultaneously record from hundreds of neurons during behavioral tasks. Several studies also leveraged genetic/viral toolboxes for the selective study of specific neuronal types and regions. Studies involving unique computational tools and new models for motor neuroscience attempted to explain and track key features of motor behavior in animal species and human subjects, as well as attempted to bring new insights into computational mechanisms of the circuitry underlying motor behavior and learning. A new understanding of muscle properties and their relation to behavior was another focus of the conference. Lastly, for several years now, researchers have been pushing to study more ecologically realistic motor behaviors. As our understanding of the neural control of movement progresses, integration across all of these approaches is critical. Moreover, as emphasized by Dr. John Kalaska in his keynote address, new advances are key to pushing motor neuroscience forward and should also be in dialogue with, and attempt to explain or reinterpret, the rich trove of previous findings and challenge established theories.

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DISCLOSURES

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AUTHOR CONTRIBUTIONS

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