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ANTICIPATORY GRIP FORCE CONTROL USING A CEREBELLAR MODEL

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Abstract—Grip force modulation has a rich history of research, but the results remain to be integrated as a neurocomputational model and applied in a robotic system. Adaptive grip force control as exhibited by humans would enable robots to handle objects with sufficient yet minimal force, thus minimizing the risk of crushing objects or inadvertently dropping them. We investigated the feasibility of grip force control by means of a biological neural approach to ascertain the possibilities for future application in robotics. As the cerebellum appears crucial for adequate grip force control, we tested a computational model of the olivo-cerebellar system. This model takes into account that the processing of sensory signals introduces a 100 ms delay, and because of this delay, the system needs to learn anticipatory rather than feedback control. For training, we considered three scenarios for feedback information: (1) grip force error estimation, (2) sensory input on deformation of the fingertips, and (3) as a control, noise. The system was trained on a data set consisting of force and acceleration recordings from human test subjects. Our results show that the cerebellar model is capable of learning and performing anticipatory grip force control closely resembling that of human test subjects despite the delay. The system performs best if the delayed feedback signal carries an error estimation, but it can also perform well when sensory data are used instead. Thus, these tests indicate that a cerebellar neural network can indeed serve well in anticipatory grip force control not only in a biological but also in an artificial system.

Key words: cerebellum, grip force, motor learning, computational model.

In our daily lives, we frequently handle objects without much thought. However, applying an adequate amount of grip force to an object being handled requires tight coordination with the dynamics of other applied forces. Let us consider the case of a robot handling an object. Its task is to simply hold it in its hand while the arm or body is being moved. The robot would ideally perform this task with minimal grip force, thus preserving energy and—more importantly—minimizing the risk of crushing the object, which is a realistic risk when, e.g. holding a Styrofoam cup. Unfortunately, using the same low amount of force constantly will not suffice, because any movement of the robot hand or arm will automatically apply a force to any object that is being handled. Because of this, inertial loads can fluctuate, possibly causing the object to slip from the robot's grasp and fall. Thus, grip force needs to be modified on occasion. Relying solely on sensory feedback to solve this problem may not be a feasible approach, since the processing of sensory data may well take too long, especially if the movements are fast. In short, the system has to anticipate changes in load force based on its movements and adjust its grip accordingly, so as to prevent to crush or drop the object it is holding.

Grip force modulation has been studied extensively in humans. Healthy human test subjects tend to hold objects with near-minimal grip force (Johansson and Westling, 1984) and adjust this force in synchrony with or even prior to the object's load force changes during movement, indicating anticipation (Flanagan and Wing, 1993; Flanagan et al., 2003). Indeed, anticipation is needed since sensory feedback arrives with a delay. This delay is also reflected by the fact that changes in motor behavior due to an unexpected event usually occur at a latency of about 100 ms (Johansson and Westling, 1987; Cole and Abbs, 1988).

Positron emission tomography (PET) scans reveal that the cerebellum plays a major role during grip force–load force coupled tasks (Boecker et al., 2005). Patients with a damaged cerebellum lack the tight coordination of grip and load force, often exerting more grip force than needed and having difficulties in timing motor actions e.g. to compensate for predictable perturbations (Babin-Ratté et al., 1999; Nowak et al., 2002; Serrien and Wiesendanger, 1999). Lesions in other areas involved in motor control such as the cerebral cortex or striatum result in paralysis or involuntary movement rather than a loss of coordination.

The cerebellum has a well-known neural structure and plays an important role in motor control in general (De Zeeuw and Yeo, 2005). Thus, it is not surprising that its network served as the basis for numerous computational models (Albus, 1975; Medina et al., 2000; Spoelstra et al., 2000; Porrill et al., 2004; Yamazaki and Tanaka, 2007). Here, we investigated the feasibility of using a cerebellar model to control grip force.

Outline

In the following sections, a brief overview of the cerebellum and interpretation of its functionality will be given first. After

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Abbreviations: BC, basket cell; CF, climbing fiber; DCN, deep cerebellar nuclei; GC, granule cell; GO, Golgi cell; IO, inferior olivary nucleus; LTD, long-term depression; LTP, long-term potentiation; MF, mossy fiber; MSE, mean squared error; PC, Purkinje cell; PF, parallel fiber; SC, stellate cell.

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that, the dataset and model used for the current work will be described. Finally, the results are presented and the current work will be discussed.

The olivo-cerebellar system

The cerebellum has two main input channels: the mossy fibers (MF) and the climbing fibers (CF). Both inputs are excitatory. The first carry signals originating from many different regions such as the pons, lower brainstem regions, and spinal cord, while the second solely carries signals from the inferior olivary nucleus (IO) in the ventral medulla oblongata. Interestingly, the inferior olive receives its inputs directly or indirectly from many of the regions that also give rise to one of the MF projections (De Zeeuw et al., 1998). Unlike the IO signals, which relay all or none signals at the Purkinje cell (PC) level, the MF signals undergo some form of recoding before arriving in the PC layer: they terminate in the granule cell (GC) layer where combinations of various MF signals are integrated with a feedback from the Golgi cells (GO) into parallel fiber (PF) signals, which in turn are carried to the PCs. Because the number of PFs is much higher than that of the MFs, it has been suggested that expansion recoding occurs (Albus, 1975; Spoelstra et al., 2000). The PFs and CFs co-terminate in the PC layer of the cerebellum, where synaptic weights are modified. It is generally believed that for this single layer of cells, the PF signals provide a current motor command and delayed sensory context, whereas the CFs may carry an error signal. This take on the cerebellum is known as the Marr-Albus-Ito hypothesis (Marr, 1969; Albus, 1971; Ito, 1984). The output of the PCs is sent to the deep cerebellar nuclei (DCN), where they merge with the input from both MF and CF collaterals and where the final output of the cerebellum is generated. Thus, the cerebellum is reminiscent of a simple perceptron and as such it may learn to apply an inverse or forward model based on its input. Inverse models enable a system to generate the desired output by producing the command that achieves a given desired state based on the current state of the system. Forward models can overcome feedback delays by predicting the result of a current command, given the current state of the system. Both models would have to be under continuous revision based on sensory input. There are indications that both types of model are used by the motor apparatus, and it has been suggested that the cerebellum may function as an inverse model that overcomes time delays using forward models (Wolpert et al., 1998).

The complexity of its cellular configurations and connections, among other things, sets the cerebellum apart from a standard perceptron. For instance, the GCs are all excitatory, while all PCs generate inhibitory output. In addition, both the granular layer and molecular layer of the cerebellar cortex have inhibitory interneurons; these include the GOs, which inhibit the GCs, and the stellate cells (SC) and basket cells (BC), which inhibit the PCs.

The interaction of the cerebellum with the IO also sets it apart from a simple perceptron. PCs inhibit both excitatory and inhibitory neurons in the DCN, the latter ones of which inhibit the IO neurons that provide the CFs to the PCs. Thus, the result is a topographically organized loop that is specific down to the cellular level. Interestingly, the olivary neurons are electrotonically coupled to each other and have a tendency to oscillate (Van Der Giessen et al., 2008). Moreover, due to their conductances, olivary neurons have a very low firing frequency with a maximum rate of 10 Hz (Llinás and Volkind, 1973) and a spontaneous activity of 2 Hz or less (Yeo and Hesslow, 1998). This arrangement implies that the cerebellum receives relatively few corrective signals, even when learning a new task.

The computational model

Input data. To provide the system with input and test the system's output, we constructed our own dataset of human grip force behavior with recordings acquired from nine healthy adult test subjects (A, B, C, D, E, F, G, H and I). During right-handed point-to-point vertical arm movements with an amplitude of approximately 30 cm, pausing after every upward and downward motion (as described in Nowak et al., 2002), participants held a manipulandum (see Fig. 1) that registered accelerations in 3D, grip force and torque on the grip force axis. The manipulandum could be outfitted with surfaces of varying roughness to establish different baseline grip force levels. These materials included, in order of increasing roughness, paper, Plexiglas and sandpaper. A total of 35 traces, each consisting of five downward and five upward movements with pauses in between, spanning approximately 20 s on average, was gathered and used. Appendix A contains an overview of the number of traces per subject and surface texture, as

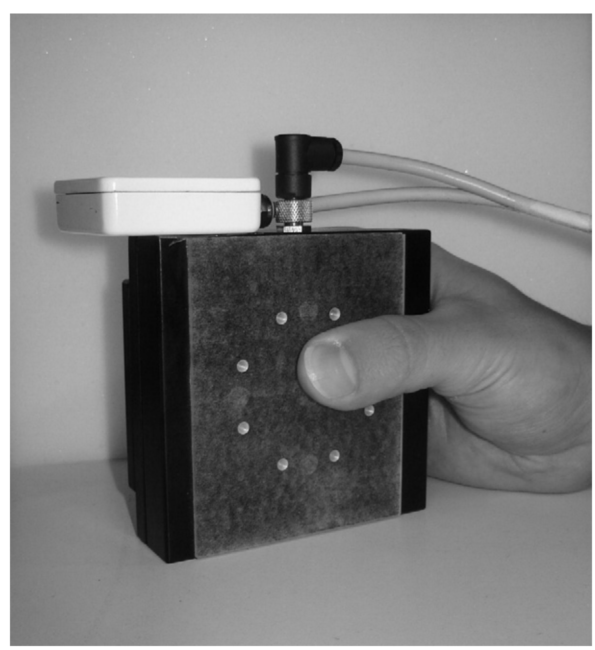

Fig. 1. The manipulandum with Plexiglas surfaces being held. The black sensor registers force and torque exerted on the gripped surfaces. The top-mounted white sensor registers accelerations in three dimensional space.