abstract expressions of motivational influence may have much in common with mechanisms, perhaps highly conserved across animal species, that modulate pursuit of concrete biological goals.

Motivational influences are incorporated in some artificial intelligence models. For example, such signals provide contextual information in an important model of reinforcement learning (Barto 1995), although the manner in which motivational signals are processed to modulate the impact of rewards and to guide action tends to be left unspecified in such models. A hierarchical account of motor control (Gallistel 1980) and recent modeling (Shizgal 1997, forthcoming) of the neural and computational processes underlying goal evaluation and selection (see decision making and utility theory) represent early steps toward formal description of the motivational influence on behavior.

See also comparative psychology; rational agency

—Peter Shizgal

References


Further Readings


Motivation and Culture

Studies of motivation try to explain the initiation, persistence, and intensity of behavior (Geen 1995; see also motivation). Culture, learned schemas shared by some people due to common, humanly mediated experiences, as well as the practices and objects creating and created by these schemas, plays a large role in nearly all human behavior. Even such biologically adaptive motivations as hunger and sex instigate somewhat different behaviors in different societies, depending on learned schemas for desirable objects, appropriate and effective ways to obtain these, and skills for doing so (Mook 1987).

The motivational effects of culturally variable beliefs can be illustrated by considering causal attribution processes. Weiner (1991) argues that we are unlikely to persist at a voluntary behavior if we have failed in the past and we attribute that failure to an unchanging and uncontrollable aspect of ourselves or the situation. Some studies show that people in Japan tend to attribute poor academic performance to insuf-
ficient effort, while people in the United States give greater weight than do their Japanese counterparts to lack of ability (Markus and Kitayama 1991; Weiner 1991). Given these assumptions, U.S. schoolchildren who receive poor grades should thereafter put less effort into their schoolwork, while Japanese schoolchildren who receive poor grades should increase their effort.

Is there a fixed, limited number of universal basic motives, which vary cross-culturally only in their strength? Or is cross-cultural variation qualitative as well as quantitative, making it impossible to delimit universally applicable basic motives? McClelland (1985; Weinberger and McClelland 1990) has argued for the first position. He has found cross-societal as well as intrasocietal differences in the average levels of such basic motives as achievement and affiliation, and he posits that human as well as other animal behavior is motivated by a limited set of stable, “implicit motives” such as these, which draw on the “natural incentive” of neurohormone release. Cantor and her colleagues (1986), by contrast, focus on idiosyncratically variable self-concepts. These are conscious, change over time, and include a variety of understandings and images, positive and negative roles and behaviors in the past and present as well as various future “possible selves,” namely, “those selves that individuals could become, would like to become, or are afraid of becoming” (p. 99). They illustrate the possible variability among such self-conceptions with the example of students preparing for a final examination. One, fearing exposure as a fraud, parties the night before the exam so that no one will attribute her failure to lack of ability. Another, having a feared “careless failure” possible self, studies very hard. The enormous variability among such self-conceptions, even within a single society, suggests the potential for limitless cross-cultural variation. Markus and Kitayama (1991), on the other hand, while continuing to link motivation to self-conceptions, posit a general distinction between societies with conceptions of self as independent of others and societies with conceptions of self as interdependent with others (see also Miller 1997). D’Andrade (1992) likewise advocates the infinite variability position. Discussing the potential for a wide variety of schemas (not just self or conscious schemas) to function as goals, he offers as a classic example from the ethnographic literature the intensity of most Nuers’ interest in cattle (Evans-Pritchard 1947).

McClelland proposes (Weinberger and McClelland 1990) that the differences between his approach and that of Cantor et al. (1986) can be resolved by treating them as describing two sorts of motivation. He provides evidence that the implicit motives he discusses are derived largely from preverbal “affective experiences” (such as early parent-child interaction in feeding, elimination control, and so on) and explain behavior over the long term and in less structured situations. In contrast, the explicit self-conceptions discussed by Cantor et al. are acquired with the mediation of language and explain choices in structured tasks, especially ones that make self-conceptions salient.

This categorization of kinds of motivation could be expanded. Neither McClelland’s nor Cantor et al.’s model accounts for the sort of behavior that is enacted because it is typical in one’s social group, making other behaviors less available for consideration, likely to provoke disapproval, or inconvenient. Examples are body language, table manners and food choices, house design, mode of dress, occupations, and forms of worship. When action follows the patterns learned from repeated observation of the typical behavior of other people like oneself, as well as social facilitation of certain ways of acting over others, it could be said to draw on routine motivation (Strauss and Quinn 1997). In many cases, routine motivation is acquired nonverbally, is internalized as implicit schemas, and is not strongly affectively charged or linked to self-conceptions. Particularly important routine motivations (e.g., schemas for being a good parent or reliable breadwinner), however, may be internalized with an explicit verbal component and linked to emotions (e.g., fear or pride) and self-conceptions, depending on how they were learned.

The different forms of motivation, and various ways in which these are learned, highlight the fact that a culture is not a single thing. In particular, cultures cannot be thought of as master programmers loading up instructions that determine people’s behavior. In every society various, not always consistent, values are proclaimed explicitly. Some of these values are the basis for motivations that socializers try to teach children, others are ignored, remaining “cultural clichés” (Spiro 1987; see also Strauss 1992; and Strauss and Quinn 1997). Finally, in addition to motivations that are deliberately instilled, there are needs and expectations derived from preverbal parent-child interactions (McClelland 1985, Weinberger and McClelland 1990, see also Paul 1990), as well as ongoing observations of the normal way of acting in one’s social group.

See also DECISION MAKING; RATIONAL CHOICE THEORY; SELF

—Claudia Strauss

References


**Further Readings**


**Motor Control**

To specify a plan of action, the central nervous system (CNS) must first transfer sensory inputs into motor goals such as the direction, amplitude, and velocity of the intended movement. Then, to execute movements, the CNS must convert these desired goals into signals controlling the muscles that are active during the execution of even the simplest kind of limb trajectory. Thus, the CNS must transform information about a small number of variables (direction, amplitude, and velocity) into a large number of signals to many muscles. Any transformation of this type is "ill-posed" in the sense that an exact solution may be either not available or not unique. How the nervous system computes these transformations has been the focus of recent studies.

Specifically, to plan an arm trajectory toward an object, the CNS first must locate the position of the object with respect to the body and represent the initial position of the arm. Recordings from single neurons in the parietal cortex and superior colliculus in awake monkeys have significantly contributed to our understanding of how space is represented. There is some evidence that in the parietal cortical areas there are retinotopic neurons whose activity is tuned by signals derived from somatosensory sources. Their visual receptive field is modified by signals representing both eye and head position. This result suggests that parietal area 7a contains a representation of space in body-centered space. Neurons representing object location in body-independent (allocentric) coordinates have also been found in the parietal cortex and in the hippocampus (Andersen et al. 1993).

To specify the limb’s trajectory toward a target, the CNS must locate not only the position of an object with respect to the body but also the initial position of the arm. The conventional wisdom is that proprioception provides information about arm configuration to be used in the programming of the arm’s trajectory. However there is experimental evidence indicating that information about the initial position of the limb derives from a number of sources, including the visual afferences (Ghez, Gordon, and Ghilardi 1993).

The current view on the formation of arm trajectories is that the CNS formulates the appropriate command for the desired trajectory on the basis of knowledge about the initial arm position and the target’s location. Recent psychophysical evidence supports the hypothesis that the planning of limbs’ movements constitutes an early and separate stage of information processing. According to this view, during planning the brain is mainly concerned with establishing movement kinematics, a sequence of positions that the hand is expected to occupy at different times within the extrapersonal space. Later, during execution, the dynamics of the musculoskeletal system are controlled in such a way as to enforce the plan of movement within different environmental conditions.

There is evidence indicating that the planning of arm trajectories is specified by the CNS in extrinsic coordinates. The analysis of arm movements has revealed kinematic invariances (Abend, Bizzi, and Morasso, 1982; Morasso 1981). Remarkably, these simple and invariant features were detected only when the hand motion was described with respect to a fixed Cartesian reference frame, a fact suggesting that CNS planning takes place in terms of the hand’s motion in space (Flash and Hogan 1985). Even complex curved movements performed by human subjects in an obstacle-avoidance task displayed invariances in the hand’s motion and not in joint motion (Abend et al. 1982). The data derived from straight and curved movements indicate that the kinematic invariances could be derived from a single organizing principle based on optimizing endpoint smoothness (Flash and Hogan 1985). It follows that if actions are planned in spatial or extrinsic coordinates, then for the execution of movement, the CNS must convert the desired direction and velocity of the limb into signals that control muscles.

Investigators of motor control have been well aware of the computational complexities involved in the production of muscle forces. A variety of proposals have been made to explain these complexities. In theory, in a multijoint limb, the problem of generation forces may be addressed only after the trajectory of the joint angles has been derived from the trajectory of the endpoint—that is, after an inverse kinematics problem has been solved. Investigations in robot control in the late 1970s and early 1980s have shown that both the inverse kinematic and inverse dynamic problems may be efficiently implemented in a digital computer for many robot geometries. On the basis of these studies, investigators have argued that the brain may be carrying out inverse kinematic and dynamic computations when moving the arm in a purposeful way.

One way to compute inverse dynamics is based on carrying out explicitly the algebraic operations after representing variables such as positions, velocity acceleration, torque, and inertia. This hypothesis, however, is unsatisfactory because there is no allowance for the inevitable mechanical