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CHAPTER 12

Embodied cognition of movement decisions: a computational modeling approach

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Abstract: This chapter presents a cognitive computational view of decision making as the search for, and accumulation of, evidence for options under consideration. It is based on existing models that have been successful in traditional decision tasks involving preferential choice. The model assumes shifting attention over time that determines momentary inputs to an evolving preference state. In this chapter, the cognitive model is extended to illustrate how links from the motor system may be incorporated. These links can basically be categorized into one of three influences: modifying the subjective evaluation of choice options, restricting attention, and altering the options that are to be found in the choice set. The implications for the formal model are introduced and preliminary evidence is drawn from the extant literature.

Keywords: attention; decision making; motor system

Introduction

Each contributor to this volume recognizes the importance of the link between the cognitive and motor systems. In practice, however, we scientists as a whole often take a reductionist approach and focus on our own specializations, assuming we can easily integrate our research into the larger schema if and when it is necessary. For example, as a cognitive psychologist, I find myself studying how the brain may process information to produce a course of action. However, rarely am I interested in how that course of action becomes physically implemented. This becomes problematic when one realizes that the other components of the system — in this case, the system being the human agent — reciprocally influence one another, and thus a complete understanding is only possible when they are considered jointly. Not to underestimate the daunting realities of such a comprehensive approach, this chapter instead aims for a more modest goal. In particular, I will outline the relevant cognitive processes that are involved with the processing of information. Then, I will offer suggestions for how the motor system can be represented as a coupled influence on these processing assumptions. Throughout, I will tend to focus on movement decisions involving the gross motor system (as opposed to saccadic decisions or key presses) to make more apparent the strong connections between motion and cognition.

Cognitive components of ball sports

I will begin with a short, focused primer on the relevant cognitive processes that I assume to

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underlie overt behavior in movement decisions. This will provide a sort of road map, not only for the remainder of the current discussion but also for the implementation of the integrative approach that I am advocating. After introducing these topics, we will be able to see how they can be formally modeled as the mental precursors for movement decisions.

Attention is the first component of cognition that will be essential for understanding athlete behavior. Attention serves as the ‘‘gatekeeper’’ of the mind, serving as a filter that determines what information is actively processed at any given moment (e.g., retained in ‘‘working memory;’’ Broadbent, 1958; Baddeley and Hitch, 1974; see Knudsen, 2007, for a review in a neuroscientific context). Our multiple senses are perpetually bombarded with input, requiring a mechanism for focusing mental efforts on some subset of immediately relevant information for subsequent processing. It is important in the context of the current discussion to realize that information comes not only from senses interacting with the world, such as vision and audition, but also proprioception such as kinesthetic and vestibular senses. Attention is what allows the athlete to hear the voice of a coach over the roar of a crowd, or to focus on the movements of team-mates setting up a play or defenders rotating positions, or to consciously modify his/her hand or arm position to perfect the topspin on a return in tennis.

Closely related to attention is the perception of the information that is currently attended. Information does not just passively enter our minds, but it is shaped in large part by our expectations, experiences, and other inherent biases. In other words, the information conveyed by our senses may be objectively defined by physical properties such as hue, pitch, or direction of motion, but our subjective interpretation of this information is what becomes the basis of thought. Decades (indeed centuries) of work in psychophysics has examined this relationship, which suggests decreasing marginal subjective response with increasing objective stimulus magnitude, summarized by the Weber-Fechner Law (see also Stevens, 1957). In other words, a constant increase in stimulus magnitude will be more subjectively impactful if it occurs at low intensities — a candle appears brighter in a cave than outside on a sunny day, and the first punch in a boxing match is likely more painful than the twenty-first.

What purpose does this influx of information serve? That is, what are the cognitive goals associated with movement decisions? Answering this question is simply a matter of working backwards in a sense, determining what cognitive operations are required to produce the behaviors that constitute a ‘‘successful’’ movement. To ground some of these concepts, it will be instructive to use a running example, such as an athletic performance. The continuous stream of an athletic contest is actually composed of a series of discrete actions, the aggregate of the choices of the athletes engaged in the sport. What is a half of soccer, really; how is it best described? By a halftime score of 1-0? No, this conveys very little information about what has taken place. In fact, it is a period of 45 minutes during which unfolds a constant series of running, passing, shooting, diving, sliding, celebrating, etc. by 22 (or more) individuals. To understand this half of play, we need to understand the contribution of each action, and to understand a single action from this series, for example, the lob pass from a midfielder to a forward, we can decompose the action into its cognitive antecedents. Specifically, driven by *attention* to different information aspects, any action can be examined as the *generation* of possible options, the *deliberation* among these options, and the ultimate *choice* of a single option.

Consider the situation facing the midfielder, who currently has the ball and dribbles across the midfield line. At this point, he/she must advance the play, and the cognitive processes that do so evolve in a sequence of events. First, he/she must survey the field and ascertain any relevant information, such as defender positions and the dynamic movements of his/her team-mates. Additional information is attended as well, ranging from relevant information from long-term memory — such as the preferences of his/her center forward and striker in receiving passes and shooting — to immediate context information such as the number of penalties on the opposing defenders and the time remaining in the half.

This attended information is then used to generate possible options — such as a lob pass to a forward, a crossfield pass to a wing player, or continuing to dribble up the sideline. Note that these options may not necessarily be explicitly generated and verbalizable at any given moment, and also that they depend largely on the (perception of the) attended information. Nevertheless, from among this set of potential options a decision is made, presumably requiring some level of cognitive processing. Perhaps a simple, repeatedly rehearsed ''if–then'' rule, based on pattern matching, is almost automatically enacted; or maybe a systematic analysis of the possible options reveals a clear ''best choice'' and results in a more explicit overt choice.

Any single choice, or action, is not performed and then lost in the chronicles of a play-by-play summary. That is, an athletic contest is indeed a series, a configural *Gestalt* that is more than the sum of its parts, something more than a collection of independent choices. Instead, these choices are decidedly *dependent*, with one affecting the next. Furthermore, each individual choice is evaluated — and by more than just tens of thousands of screaming critics. Each individual must assess the functional outcome of his/her actions, and thereby learn about his/her successes or failures. Cognitively, performance feedback becomes the impetus for modifying future behavior, through modifying future option generation, deliberation, and choice strategies. A poor choice in one instance is less likely to be generated as a viable option in future instances, less likely to be favored during deliberation even if it is considered, and less likely to be chosen even if it is momentarily favored.

Motoric influences on cognition

In an abstract sense, and in sterile laboratory conditions, these concepts of attention, perception, option generation, deliberation, choice, outcome assessment, and learning have been studied for decades by cognitive psychologists. However, there is a huge discrepancy between the study of learning shape and color patterns by undergraduates and the learning of successful shots on goal by highly motivated athletes in sports. Not only is the athletic domain different (i.e., realistic), and the athlete more emotionally involved, but the *physical* immersion of the athlete in the athletic contest suggests the importance of the physical position and movement. Recently, a successful research paradigm in naturalistic decision making has emerged that addresses some of the deficiencies of laboratory research (Zsambok and Klein, 1997). This work does involve decision agents in their real environments, but has not necessarily highlighted the role of physical embedment.

This is a critical point because although the discussion thus far has described the cognitive components that lead to observable action, the link is really bidirectional. In particular, there are a number of findings that suggest we as theorists must acknowledge the simple fact that a decision is ultimately one of movement. Work on cognitive tuning has shown that indeed the cognitive processes described above can be greatly influenced by the position of the body's muscles and limbs (e.g., Friedman and Förster, 2002). Furthermore, obvious influences stem from factors such as physical orientation: if one is facing the left side of the field, then information from this direction is more salient and thus more influential in subsequent deliberation, and options are more likely to be generated within this restricted range.

Perhaps most importantly, especially in situations such as athletic contests, what one would cognitively wish to perform is not necessarily attainable physically. Due to constraints on one individual's abilities, perhaps the ''best'' solution or decision in a given situation is beyond the skill level of the individual (or sometimes, any individual). Therefore, even though one may know what the best choice is, it may not correspond to an option that is available to the specific decision maker. Maybe an opponent in tennis has immense trouble handling backhand returns, but if I am incapable of producing a decent backhand return then this option is not viable, even if I know that it would be the ''best'' against this opponent. In sum, I conceptualize the influence of the motor system *during* decision-making deliberation as being manifest in one or more of three primary ways: (a) priming or modifying the subjective evaluation or perception of courses of action, as in cognitive tuning; (b) restricting one's momentary focus of attention, based on physical orientation; and (c) altering the options that are to be found in the choice set, or at least those that are seriously considered to be enacted.

Finally, it is important to acknowledge the performance of the motor system *after* cognitive processes have produced a ''winner'' or intended course of action. Cognitive models rarely consider the direct translation of thought into action. That is, although a cognitive model may predict which option is favored as a result of cognitive operations — such as the careful weighing of pros and cons, or simply the ''gut'' reaction (i.e., instinct) that leads one to prefer a specific option — the physical implementation of this choice is seen as a foregone conclusion. It is typically assumed that cognitive decisions directly and infallibly produce the corresponding action. However, a ball is not passed, kicked, hit, or thrown simply by willing it to happen, but rather as the result of physical action. Thus, the motor system can be seen as taking a (cognitive) input and producing the physical output. This process is also prone to unique sources of error — the playmaker may overshoot the pass to one team-mate, resulting in possession by another (unchosen) team-mate. Granted, this still assumes a ''privileged'' status of the cognitive system and relegates the motor system to a serially secondary process that is undoubtedly too simplistic. Other approaches assume a more direct role of the motor system (and even downplay the cognitive role altogether in presuming perception–action coupling, see Chapter 4: Perceiving and moving in sports and other high-pressure contexts). Future extensions to the framework introduced here will need to better specify the bidirectional nature of these links and the more central role played by the motor system.

The remainder of the chapter will introduce a formal approach to incorporating these motoric influences on decision behavior, with the caveat that any attempts made here are exploratory. In particular, I will outline a general framework for modeling decision making that has been very successful in traditional (laboratory) decision tasks. Then, I will detail two distinct extensions to this framework to accommodate the two key notions introduced here: (a) the explicit influences of the motor system on the cognitive processing of information; and (b) the subsequent influences upon the observed decision (overt action) attributable to the motor system. It is a challenging task to incorporate these important components, but one that will lead to a more comprehensive view of athlete behavior and other movement decisions.

Formal modeling of human movement decisions

Aristotle is often credited with the first popular model of planetary/stellar motion, which placed the earth at the center of the solar system and suggested spherical planetary/stellar orbits. Because this model was unable to account for several observable phenomena, it required extensive modification. This led to the development of Ptolemy's rather complicated geocentric model (with input from Hipparchus), requiring 13 books to present fully. This mathematical model required several specific geometric devices to explain observed motions. It was Copernicus, circa 1543, who advanced the notion of a sun-centered (heliocentric) model. This model provided a much simpler and parsimonious explanation for the observed data by focusing on a wholly different approach. It was the Copernican model that was expanded on by Galileo, Kepler, and Newton to become what we know today to be the correct description of planetary motion. Similarly, I advocate a Copernican revolution of sorts — more properly a computational revolution — in the study of human decision making.

In the field of decision making, the evolution of contemporary models can similarly be traced by examining the failure of popular models in accounting for aspects of behavioral data. Each failure (e.g., ''bias'') spurred subsequent modification of the basic model (expected utility theory) to accommodate the ''anomalous'' empirical results. However, the general approach of the basic model has been retained, resulting in a present-day patchwork of mechanisms built in to the basic model to explain mounting evidence against expected utility computations. Metaphorically, decision researchers are still clinging to the geocentric (algebraic) model rather than adopting a more parsimonious heliocentric (computational) approach.

The "basic model," expected utility theory, is based on an algebraic calculation of evidence in favor of competing courses of action. Specifically, theories in this tradition specify a utility function that transforms objective values (e.g., monetary outcomes of gambles) into subjective values, called utilities; a weighting function that transforms objective event probabilities (e.g., chance of each gamble outcome) into subjective assessments, or decision weights; and rules for utilizing the transformed information. Typically, these rules involve combination (multiplication) of weight and utility for a given outcome or consequence, as well as integration (addition) of weighted utilities in computing a holistic value for each possible alternative or action. The option with the highest holistic value is then chosen. The most popular current incarnations of the basic model are termed rank-dependent utility (RDU) models, such as prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

In contrast, computational models formally describe the transformation of information into action, not just the relations among inputs and outputs, and thus produce precise, quantitative, testable predictions about mental processes. Cognitive modeling, in particular, has enjoyed a recent surge of popularity. The "cognitive revolution" during the last half of the last century has permeated much of psychology, promoting cognitive mechanisms to describe behavior. In particular, there has been an increase in attention to the information processing that underlies human behaviors, in contrast to the behaviorist viewpoint of the first half of the century. That is, rather than simply viewing behavior as conditioned responses, or matching of situations to actions, the cognitive processing that drives these responses is taken into consideration. The increased interest in cognitive modeling is due in large part to the success these models have enjoyed across domains outside of mainstream cognitive psychology (i.e., beyond memory, language, categorization, etc.). This advance is not yet apparent to the same degree in examining decision making and other behaviors with motor consequences.

In decision making in particular, computational models are only beginning to become the "state of the art" in a field long dominated by utility theories and assumptions of human rationality and adherence to the laws of probability. Next, I will describe a modeling framework that is arguably the most successful in accounting for empirical results in the decision-making literature. These sequential sampling models have been applied to binary choices (Busemeyer and Townsend, 1993); multiattribute decisions (Diederich, 1997), multialternative settings (Roe et al., 2001); influences of motivational and drive states on decision making (Busemeyer et al., 2002); decisions under time pressure (Diederich, 2003); other response modes such as prices (Johnson and Busemeyer, 2005); and many more (see Busemeyer and Johnson, 2004, 2008, for reviews). Furthermore, this same class of models has been successful across many content domains in cognitive psychology, including perceptual discrimination (Link and Heath, 1975), recognition memory (Ratcliff, 1978), probabilistic inference (Wallsten and Barton, 1982), and others.

Sequential sampling model representation

Sequential sampling models assume that deliberation during a decision occurs at some subconscious level, rather than as an exhaustive and calculated assessment of the benefits and drawbacks of each option. That is, in contrast to the most popular conceptualizations of choice (utility theories), it is unlikely that athletes compute expected values during an athletic contest. As an alternative to this view of "economic" decision making, sequential sampling models suggest that information is sampled over time, which results in increases or decreases in the relative preference for each option.

First, the sequential sampling model allows for a non-neutral *initial preference*, meaning there may be preference for a particular option before any task-relevant information is considered. The midfielder may exhibit some favoritism for a particular team-mate, regardless of the specific situation. From this point, information is sampled (attended) over the course of deliberation. At one moment, the midfielder may be focused on the need to score a goal and consider the scoring potential of different actions, at the next moment he/she may be focused on playing conservatively to retain possession of the ball.

Psychologically, the sequential sampling model assumes that the attended information brings to mind affective reactions to each option, largely based on previous experiences (if available) and/or implicit predictions of potential outcomes. If the midfielder considers defender distances, and one team-mate is closely guarded, this may produce a negative reaction towards passing to this team-mate based on recalled instances of turnovers or the predicted possibility of a turnover. If he/she considers the fact that his/her team is down with little time remaining, then passing to team-mates in scoring position will be evaluated positively. Affective *valences* such as these are produced for each option, at each moment in time, and are integrated over time to derive a *preference state* for each option. The evolution of preference states proceeds as additional information is considered over the course of deliberation. At some point an option must be selected — after all, the midfielder must decide what to do at some point, or stand near the midfield line paralyzed with inaction! Sequential sampling models introduce a *threshold*, or level at which an option is considered "good enough," to determine choice. As preferences for each relevant option accumulate, the midfielder eventually must decide that the preference for one single option is strong enough to deserve action. This model has accounted for a variety of findings that have challenged other decision models (Busemeyer and Johnson, 2008) and has been specifically applied to sports tasks (Johnson, 2006).

The intuitive model description above can be precisely modeled as a dynamic system to afford quantitative predictions. Formally, I will here follow the presentation of Roe et al. (2001) that allows for any number of options, described by any number of attributes (see also Diederich and Busemeyer, 2003, for an excellent practical tutorial on how to apply these models to data). Assume a decision maker, such as our midfielder, is considering some m number of actions (e.g., lob pass to center forward), each described by n attributes (e.g., safety/conservativeness, scoring potential, adherence to game plan, etc.). These may be represented as an $m \times n$ matrix, $\mathbf{M}$, where the "value" of option i on the j^{th} attribute is found at m_{ij}. For example, if A = "lob pass to center forward," and B = "dribble to the right," then perhaps A has a higher scoring potential ($m_{\text{A,scoring}} > m_{\text{B,scoring}}$) whereas the latter is less risky ($m_{\text{A,safety}} < m_{\text{B,safety}}$). For mathematical tractability when dealing with attributes that may vary in range, we typically assume that each column of $\mathbf{M}$ is divided by the maximum value in that column. This makes the contribution of attributes uniform that may otherwise vary greatly. For example, attributes for a new car decision may include price, which is measured in tens of thousands, as well as fuel economy in liters/kilometer, which is measured by values less than one!

I propose a significant extension to this representation that is especially relevant to dynamic situations such as movement decisions in general, and athletics in particular. Whereas Roe et al. (2001) introduce the $\mathbf{M}$ matrix as static over the course of the decision task, I propose relaxing this assumption of time-homogeneity and allow for $\mathbf{M}(t)$. Specifically, the dimensionality of $\mathbf{M}(t)$ may change over time as new options are considered and added to the choice set. In contrast to laboratory tasks where the choice options are a closed set explicitly presented to the participant, in real situations potential actions must often be generated "on the fly" over time. For example, rather than having a preconceived set of options in mind, a playmaker dynamically generates these options as he/she scans the field during a play and advances the ball up the field. Option generation has not received considerable attention in decision making and thus has not entered into formal models (but see Gettys et al., 1987; Klein et al., 1995; Johnson and Raab, 2003; and Thomas et al., 2008 for notable exceptions). Here, I simply assume that the $1 \times n$ vector of attribute values for an option is concatenated to the choice set matrix $\mathbf{M}(t)$ at the time t when it is generated. It is beyond the scope of this chapter to detail the option generation process proper, detailing which options are generated and when (but see Johnson and Raab, 2003; Raab and Johnson, 2007a, b for our work on this topic).

The sequential sampling models described here assume that these values are evaluated relatively, rather than absolutely. That is, an action with a very high scoring potential will appear very favorable compared to an action with a low scoring potential, but only slightly better than an action with a scoring potential that is similar. This relative comparison, or contrast operator, is performed mathematically with an $m \times m$ matrix $\mathbf{C}$ that typically takes the form of ones along the main diagonal, and $-(1/m-1)$ as all off-diagonal elements. In other words, when we take the matrix product $\mathbf{C} \cdot \mathbf{M}(t)$ it converts the value of action i on attribute j from its absolute value to a value that is scaled by the average of all other actions $k \neq i$ on attribute j. Hereafter, we assume this contrast operator has been applied and will simply refer to the product $\mathbf{C} \cdot \mathbf{M}(t)$ as $\mathbf{M}(t)$.

Sequential sampling models do not assume that all the information (i.e., attributes) for each potential action are simultaneously weighed and considered. Rather, they describe the shifts in attention across different pieces of information or attributes over time. Typically, they assume that at any given moment, attention focuses on a single attribute in an all-or-none fashion. This is modeled by an $n \times 1$ attention weight vector $\mathbf{W}(t)$, which models current attention to attribute k as $w_k(t) = 1$, $w_j(t) = 0$, for all $j \neq k$. This may be a simplifying assumption, based on the ability of working memory to process multiple pieces of information, and the debates found in an entire literature on divided attention. In any case, we retain this assumption for the moment, but acknowledge the possibility that multiple nonzero elements could exist in $\mathbf{W}(t)$, representing the proportion of attention to each attribute at each moment, with $\Sigma\, \mathbf{W}(t) = 1$.

The mechanism for these momentary shifts in attention varies across sequential sampling models. Busemeyer and Townsend (1993) and Roe et al. (2001) make the simplifying assumption that the focus of attention — that is, the location of the "1" element in $\mathbf{W}(t)$ — changes stochastically over time based on the relative importance or "weight" of each attribute. For example, if scoring potential is the most important attribute, and furthermore is equally as important as all other attributes combined, then this would be formally modeled as $\Pr[w_{scoring}(t) = 1] = 0.50$, for all t. Diederich (1997) has developed sequential sampling models that specify a particular (rather than stochastic) order by which attributes are considered. Especially intriguing is the possibility of measuring overt visual attention as a proxy for covert attention to be input to Diederich's (1997) models; the use of eye-tracking methods offer promising potential in this pursuit (Raab and Johnson, 2007a, b; Johnson and Raab, 2008).

Johnson and Busemeyer (2008) have developed a computational model of the attention-switching processes assumed to operate for people in more tightly controlled (although more abstract) experimental settings, involving choices in the laboratory among sets of gambles. However, the same basic principles can be applied to the practical domain of movement decisions in athletics. Essentially, the model suggests that dynamic patterns of attention can be wholly specified by considering (1) what attribute is first considered, and (2) the conditional probability of attending to each attribute, given the current focus of attention. Formally, this suggests attention switching is a Markov process defined by transitions in attention over time. Application to any task simply requires specifying the probability that each piece of information is initially considered, and the conditional transition probabilities.

In the soccer example, the first attributes considered can be based on factors such as: immediate context — for example, if it is late in the second half and one's team is trailing, then scoring potential is more likely to be considered first, or a rapidly approaching defender may trigger initial thought of safe passing options; perceptual salience — attributes that are more prominent are likely to be considered first; or previous experience — past situations, especially those with successful outcomes or those frequently occurring (e.g., during training), may prompt initial consideration of specific attributes. Then, the conditional probability of considering the next attribute could depend on factors such as the degree of similarity between attributes, or specific attentional patterns acquired during training (e.g., the order of a quarterback's "reads" in American football).

At this point, we have specified the attributes that describe each option, $\mathbf{M}(t)$, as well as the mechanism of shifting attention across these attributes, $\mathbf{W}(t)$. Simple matrix multiplication of $\mathbf{M}(t) \cdot \mathbf{W}(t) = \mathbf{V}(t)$ produces an $m \times 1$ vector of the relative attribute values that are considered at moment t, collectively referred to as the momentary *valence*. This describes the subjective assessment of each option, relative to other options, at any given moment in time based on the currently attended attribute. As attention shifts over time among attributes, the momentary valence changes as well. At one moment attention may be focused on scoring a game-winning goal, in which case those options with a high scoring potential will be evaluated more favorably, and the momentary valence at that point will reflect this. At the next moment, perhaps attention shifts to the need to retain possession of the ball to prevent a game-winning goal by the other team, in which case those options with higher "safety" or less riskiness will be evaluated more favorably in $\mathbf{V}(t)$. As the momentary valence changes over time, sequential sampling models assume that these are collected and accumulated into a momentary preference state, $\mathbf{P}(t)$. In particular, I assume the *preference state* at time t is a simple linear combination of the previous preference state and the current valence input: $\mathbf{P}(t) = \mathbf{SP}(t-1)+\mathbf{V}(t)$, where $\mathbf{S}$ is an $m \times m$ matrix that allows for growth/decay of the previous preference state, as well as dependencies across options (see Roe et al., 2001, for a discussion of $\mathbf{S}$, including psychological interpretations).

I have now described how one's preference over a set of options in a movement decision evolves over time, driven by shifting attention to different attributes of the options. To specify the model fully, I need only determine the beginning and end of this process. In particular, the initial state of the model, or the *initial bias* of the decision maker prior to any information acquisition, is represented as an $m \times 1$ vector, $\mathbf{P}(0) = \mathbf{z}$. For example, if there is no initial preference for any options, then all $z_i = 0$. Alternatively, if the midfielder has a tendency to "dribble first, pass later," then that could be modeled by a higher vale for z_{dribble} than any other option. Perhaps the midfielder has a favored forward player to whom he/she has a strong rapport and a marked predisposition for passing; in this case, the option of passing to that player might have an elevated z_i relative to other options.

Finally, a method must be used to end deliberation. That is, I have described how the preference state changes over time, but at some point a decision must be made and action must be taken, or the midfielder will find himself/herself constantly thinking and never acting! Intuitively, there is typically no need to process attribute information exhaustively during a decision. Especially for dynamic situations such as the midfielder's, the information could readily change and thus there could arguably be a functionally infinite amount of potential information. To prevent paralyzing indecision, sequential sampling models specify a *threshold* preference level, or a level of preference which is "good enough" to justify selecting an option. Formally, a free parameter θ denotes the necessary preference whereby $P_i(t) > \theta$ produces a choice of option i at time t. Although this value is typically held constant (e.g., Busemeyer and Townsend, 1993), one could imagine situations where it may decrease over the course of deliberation, or be defined as a relative rather than absolute value.

Incorporating motor system influences on cognition

The previous section introduced a formal representation of movement decisions via a computational (sequential sampling) model. This model has been applied to many ''purely cognitive'' decisions where the only required response was a key press or a mouse click. How could — or *should* — the model be modified to reflect the realities of an agent that is situated physically in a decision situation? Recall that I advocated for three primary routes by which the motor system could directly impact the cognitive decision-making apparatus: (1) changes in the subjective perception of value; (2) changes in attentional focus; and (3) changing the actions in the choice set. I now discuss how to incorporate each of these factors in turn.

First, the motor system may be responsible for changes in the perception of the attributes of the choice options. For example, if the motor system is fatigued, then perhaps this changes the perception of attributes associated with some options. A long lob pass would be perceived as a riskier maneuver if the midfielder knew that his/her body might not physically be able to produce such a pass. Poor calibration during a given contest may lower the midfielder's confidence in his/her shooting ability, and thus lower the scoring potential associated with any direct shots on goal. A more provocative method for formally incorporating the influence of the motor system is to assume that the motor system itself contains attributes. That is, although the current $\mathbf{M}$ is assumed to be perceptual, this is not a requirement or a restriction. Various attributes that could define an option relevant to the motor system, such as physical effort required or likelihood of proper physical implementation, could be collected as distinct entries (columns) in $\mathbf{M}$. In this case, motoric influences such as fatigue would be represented independently from other considerations, meaning that the subjective assessment of physical effort required to enact an option would be modified, but the unconditional scoring potential of the option would not. The differences between these formal representations would become apparent based on how attentional shifts proceed. For the former case, where the motor system directly changes the option's ''perceptual'' attributes such as scoring potential, then any attention to this attribute would involve a motoric tempering of the attribute value and thus the momentary valence. In the latter case, attention to perceptual attributes would leave the valence unaffected by the motor system, and only explicit attention to motoric attributes could produce an influence.

Second, the motor system could directly impact shifting attention, the driving force of the sequential sampling model. For example, perhaps fatigue does not only diminish values (either perceptual or motoric), but it may also increase the likelihood of attending to these values. Assume for a moment that we represent motoric dimensions independently in $\mathbf{M}$, such as the physical effort to enact option i as $m_{i,\text{effort}}$. Early in an athletic contest, the midfielder may pay very little attention to the effort required to produce a certain movement, such as a long lob pass; however, after running for 80 minutes this may be a much more salient dimension on the midfielder's mind. In this case, $\Pr[w_{\text{effort}}(t) = 1]$ would be much larger at the end of the contest than at the beginning. Changes in attentional focus based on physical constraints could also make some options more likely to be considered than others. For example if the midfielder is facing to the left then one might expect greater assessment of options that are on the left — although, of course, knowledge of unseen players' positions and habits would not preclude other possibilities. In any case, this could be performed in the model by selectively ''zeroing out'' or greatly diminishing values on a given row of $\mathbf{M}(t)$ at a given moment that do not match the momentary physical orientation. Johnson and Raab (2008) formally model these sorts of spatial dependencies in visual attention in the context of a sampling model to predict choices in handball.

Third, and also in line with this notion of modifying rows of $\mathbf{M}(t)$, is the addition or deletion of rows within $\mathbf{M}(t)$ due to physical impossibility. This would formally restrict cognitive appraisal of options to those options that are able to be instantiated physically, obviating the potential paradox of preferring or selecting an option that cannot be carried out. Even if an option i is generated at time t when facing in one direction, if the midfielder is in a different position and orientation at time t' which makes this option physically unfeasible, then we would assume the corresponding row of values $m_{i.}$, $(t') = 0$. If at a later point t'' this action could again be completed, then $m_{i.}$, (t'') would return to their original values. Although mathematically the addition of a row due to (cognitive) option generation would produce the same result as this physical ‘‘reacquisition’’ of a potential action, only the physical constraints are assumed to result in the deletion or ‘‘zeroing out’’ of values in $\mathbf{M}(t)$.

There are several auxiliary assumptions that could be relaxed in the sequential sampling model to accommodate the unique nature of movement decisions in real environments. For example, perhaps attention does not shift among attributes, but across *options*. In other words, $\mathbf{W}(t)$ would become an $m \times 1$ column vector that would indicate the current option under consideration. This would make more concrete some of the other assumptions of motoric influence as well, such as increased attention to physically congruent options. Physical fatigue or other factors may adjust the decision threshold bound θ as well, such as by requiring less support or accumulated preference for an option before action is initiated. The possibilities outlined in this section, as well as others, are intriguing avenues for future work in using sequential sampling models for movement decisions. Ideally, one could perform model comparisons to determine which candidate implementations are most successful at reproducing choices and response times of real movement decisions (see Raab and Johnson, 2004, for an analogous quantitative application of the sequential sampling model to test alternative hypotheses for decisions in basketball).

Motor system realization of cognitive intentions

The previous section detailed how to incorporate motoric influences on deliberation formally. However, it did not provide any insight into how the (cognitively) selected action was implemented. That is, although the attainment of a threshold level of cognitive preference for an option may dictate which action is preferred, and when, it does not describe how this action is physically implemented, or how long this action production takes. One can imagine additional influences during this stage as well that may produce an action distinctly different than the one intended. Especially in behavioral science, where we only have access to observed actions, we typically assume that those observations reveal the intentions of the agent. However, this need not always be the case. The motor system can exhibit its own characteristic sources of error that produce significant deviations from expected or planned behavior. The tennis star never intends to hit a ball 5 cm beyond the edge line, and the action ‘‘shoot ball 1 m over cross bar’’ was probably not the first action to reach a decision threshold during a soccer player’s penalty kick deliberation. Only by appreciating this fact of the motor system (at least), and ultimately modeling it explicitly (at best), can we hope to truly capture in an explanatory framework decisions involving complex, coordinated movements. This is the biggest challenge facing a formal model, which for now will regrettably have to be relegated to a simple ε appended to the cognitive model.

Bridging the mind–body gap

The examples from previous work surveyed above illustrate a steady production of studies and modeling endeavors that are helping us to understand the cognitive processes underlying movement decisions better. These processes are summarized and illustrated in Fig. 1. Options are generated dynamically, adding options to the choice set $\mathbf{M}(t)$ as time elapses. Each option (larger circle) is conceptually decomposed into a collection of its relevant attributes (smaller circles, $m_{i,j}$). At any moment in time, attention is focused on some aspect or attribute of each choice option, according to the attentional dynamics in $\mathbf{W}(t)$ described earlier. This would result typically in a common feature across options receiving attention (as illustrated by the dark lines in Fig. 1), but could also be represented by all features of one option receiving attention, as proposed in the model extension suggesting attention shifts across options (rows in $\mathbf{M}(t)$). The current focus of

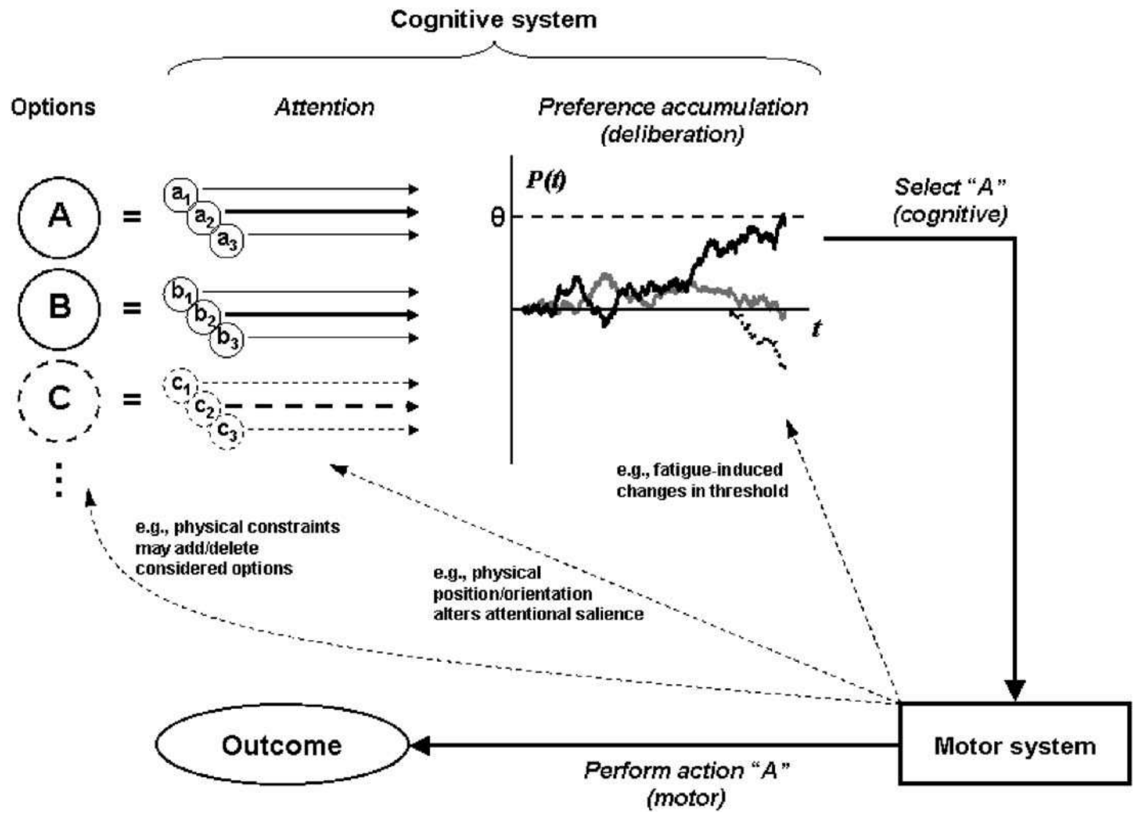

Fig. 1. Integrated model of cognitive and motor systems regulating athlete behavior. Option generation appends possible choice alternatives to the choice set, such as the newly generated option "C." Attention to specific attributes of these options (currently shown as attention to the second attribute of each option, represented as dark lines) drives preference accumulation over time for each option. The first option to reach a threshold level of preference (here, option "A") is selected as the output of the cognitive system. This selection drives the motor system to enact the movements associated with choice of the option. The resulting outcome is used for learning, which affects subsequent cognitive and motor performance. Note that influences (dashed lines) between the cognitive and motor system, and within the cognitive system, also appear. See text and related references for details of each component.

attention determines how the preference for each option increases (or decreases) during that instant, shown in the plots of option preferences, $P_i(t)$, against time, t. For example, in Fig. 1, the illustrated preference accumulation process suggests that during roughly the second half of deliberation, the attention allocation was towards information that favored option "A," shown as the dark trajectory. This is inferred because this preference trajectory increased more than preference for option "B," the gray trajectory, or option "C," the dotted trajectory. The option "C" was generated during the final moments of deliberation, and as a result this preference trajectory does not have a history earlier in the deliberation process. Option "A" is the first to reach the preference threshold (the dashed, horizontal line θ), resulting in choice of "A" and a corresponding response time prediction.

An important consideration in Fig. 1 is that the (cognitive) choice of "A" does not necessarily result in initiation of action that supports this choice. That is, although the midfielder may decide that passing to the striker is the best alternative, enacting the physical motions to bring about or realize this choice is not a deterministic extension of the cognitive appraisal, as mentioned earlier in this chapter. Issues such as motor memory, muscle fatigue, and calibration error, among a host of others factors, can result in an outcome that does not correspond to the one preferred by the cognitive system; these influences are the purview of movement scientists. Only the input is specified in the current iteration of the model, with the motor mapping of the cognitive input to the physical outcome to be more precisely detailed.

One facet that is important but withheld from Fig. 1 (for clarity) is the role of feedback (which would emanate from the ‘‘Outcome’’ node to the motor and cognitive systems). Feedback leads to cognitive adjustment, including the likelihood of generating specific options in subsequent situations, or the guidance of attention, or the operation of the mechanisms of deliberation (e.g., initial preference for different options, shown in the plot in Fig. 1 as being equal and zero). However, feedback can also influence subsequent motor system performance, such as ‘‘fine-tuning’’ of one’s shot in basketball. While these types of feedback extensions are unidirectional, perhaps the most important form of bidirectional links in the context of the current discussion is the ongoing crosstalk between the motor system and the cognitive system. This feature is manifest most explicitly in the guidance of attention. Movement or body position in a specific direction will obviously bias attention in the given direction, for example. However, there are more subtle influences on cognition as well, as evidenced by work on motor ontology and cognitive tuning (e.g., Friedman and Förster, 2002; Gallese and Metzinger, 2003).

The mechanisms of motor ontology (i.e., how the motor system constrains high-level mental phenomena, such as through goal representation) are not yet fully understood, and a formal model fitting the relevant data is still missing. For example, under the influence of a negative signal a decision might be reached later, and fewer options might be generated, compared to the influence of a positive feedback signal (see Raab and Green, 2005 for empirical evidence). In the model framework for deliberation introduced earlier, these influences are most predictive in their effect on initial preferences. In a context where a fast decision is made, it is not surprising that initial preferences (i.e., beginning preference closer to threshold) has the highest impact because less external and internal information is integrated. That is, the preference formation is highly influenced by the initial bias value and to a smaller amount by the signal values. In this framework, in short, proprioceptive feedback signals the cognitive system and thereby alters the preference of options.

Conclusions

I have provided an introduction and brief survey of the use and usefulness of cognitive modeling of behavior in general, and decision making in particular, to movement behaviors. The cognitive component of athletes’ decision behavior is an important consideration that is only recently becoming appreciated. However, the role of cognition in ball sports obviously cannot be removed from the situation in which it is embedded, nor from the physical system which produces the relevant behaviors (motions). Thus, it is important to consider models of athlete behavior from a perspective that recognizes the interactive links between the body, mind, and environment. Recent work on ‘‘motor cognition’’ has begun to make strides in this direction as well.

I have presented initial attempts at formally modeling the cognitive processes that give rise to movement behavior, as well as the relationship between cognitive and physical systems. Theoretically, I advocate the use of sequential sampling models that have been successful in explaining cognitive aspects of decision making. Here, I showed how to extend these models to incorporate motoric influences. Another key advantage of these models is their ability to be cast in terms of potential neural substrates and thereby link to the neuroscientific evidence on decision making (see Schall, 2004, and Chapter 23: Juggling with the brain — thought and action in the human motor system, for excellent reviews; see Chapter 17: Perceptual decision making: a bidirectional link between mind and motion, for neuroscientific treatment of perceptual decision making; see Busemeyer et al., 2006, for a discussion specific to sequential sampling models).

Empirically, I have selectively investigated the relevant cognitive process including how movement options are generated and selected (Johnson and Raab, 2003); how models of mental deliberation incorporating individual differences and cognitive traits can predict movement decisions (Raab and Johnson, 2004); general applications and advantages of cognitive modeling to movement decisions in sports (Johnson, 2006); and methods for illuminating these cognitive processes through measurements of visual attention via eye tracking (Raab and Johnson, 2007a, b; Johnson and Raab, 2008). This chapter has begun to integrate these efforts in hopes of ultimately developing a model that considers jointly proprioceptive information, perceptual inputs, and cognitive processing in models of movement behavior. Through continued integration and refinement, I am confident that cognitive models, when connected bidirectionally to our knowledge of the human body, will provide a comprehensive understanding of movement behaviors.

References

Baddeley, A., & Hitch, G. (1974). Working memory. In G. A. Bower (Ed.), *Recent advances in learning and motivation* Vol. 8, (pp. 47–90). New York: Academic Press.

Broadbent, D. E. (1958). *Perception and communication*. New York: Oxford University Press.

Busemeyer, J. R., Jessup, R. K., Johnson, J. G., & Townsend, J. T. (2006). Building bridges between neural models and complex decision making behavior. *Neural Networks*, *19*, 1047–1058.

Busemeyer, J. R., & Johnson, J. G. (2004). Computational models of decision making. In D. Koehler & N. Harvey (Eds.), *Blackwell handbook of judgment and decision making* (pp. 133–154). Oxford: Blackwell.

Busemeyer, J. R., & Johnson, J. G. (2008). Micro-process models of decision making. In R. Sun (Ed.), *Cambridge handbook of computational psychology* (pp. 302–321). Cambridge: Cambridge University Press.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*, 432–459.

Busemeyer, J. R., Townsend, J. T., & Stout, J. C. (2002). Motivational underpinnings of utility in decision making: decision field theory analysis of deprivation and satiation. In S. Moore (Ed.), *Emotional cognition* (pp. 197–218). Amsterdam: John Benjamins.

Diederich, A. (1997). Dynamic stochastic models for decision making under time constraints. *Journal of Mathematical Psychology*, *41*, 260–274.

Diederich, A. (2003). MDFT account of decision making under time pressure. *Psychonomic Bulletin & Review*, *10*, 157–166.

Diederich, A., & Busemeyer, J. R. (2003). Simple matrix methods for analyzing diffusion models of choice probability, choice response time, and simple response time. *Journal of Mathematical Psychology*, *47*, 304–322.

Friedman, R., & Förster, J. (2002). The influence of approach and avoidance motor actions on creative cognition. *Journal of Experimental Social Psychology*, *38*, 41–55.

Gallese, V., & Metzinger, T. (2003). Motor ontology: the representational reality of goals, actions and selves. *Philosophical Psychology*, *16*, 365–388.

Gettys, C. F., Pliske, R. M., Manning, C., & Casey, J. T. (1987). An evaluation of human act generation performance. *Organizational Behavior and Human Decision Processes*, *39*, 23–51.

Johnson, J. G. (2006). Cognitive modeling of decision making in sports. *Psychology of Sport and Exercise*, *7*, 631–652.

Johnson, J. G., & Busemeyer, J. R. (2005). A dynamic, stochastic, computational model of preference reversal phenomena. *Psychological Review*, *112*, 841–861.

Johnson, J. G., and Busemeyer, J. R. (2008). A computational model of the process generating decision weights.

Johnson, J. G., & Raab, M. (2003). Take the first: option-generation and resulting choices. *Organizational Behavior and Human Decision Processes*, *91*(2), 215–229.

Johnson, J. G., and Raab, M. (2008). In the eye of the beholder: Modeling intention from attention.

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, *47*, 263–291.

Klein, G., Wolf, S., Militello, L., & Zsambok, C. (1995). Characteristics of skilled option generation in chess. *Organizational Behavior and Human Decision Processes*, *62*(1), 63–69.

Knudsen, E. I. (2007). Fundamental components of attention. *Annual Review of Neuroscience*, *30*, 57–78.

Link, S. W., & Heath, R. A. (1975). A sequential theory of psychological discrimination. *Psychometrika*, *40*, 77–105.

Raab, M., & Green, N. (2005). Motion as input: a functional explanation of movement effects on cognitive processes. *Perceptual and Motor Skills*, *100*, 333–348.

Raab, M., & Johnson, J. G. (2004). Individual differences of action–orientation for risk-taking in sports. *Research Quarterly for Exercise and Sport*, *75*(3), 326–336.

Raab, M., & Johnson, J. G. (2007a). Expertise-based differences in search and option generation strategies. *Journal of Experimental Psychology — Applied*, *13*, 158–170.

Raab, M., & Johnson, J. G. (2007b). Implicit learning as a means to intuitive decision making in sports. In H. Plessner, C. Betsch, & T. Betsch (Eds.), *A new look on intuition in judgment and decision making* (pp. 119–133). Mahwah, NJ: Lawrence Erlbaum Associates.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59–108.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative decision field theory: a dynamic

connectionist model of decision making. *Psychological Review*, *108*, 370–392.
Schall, J. D. (2004). On building a bridge between brain and behavior. *Annual Review of Psychology*, *55*, 23–50.
Stevens, S. S. (1957). On the psychophysical law. *Psychological Review*, *64*, 153–181.
Thomas, R. P., Dougherty, M. R., Sprenger, A., & Harbison, J. I. (2008). Diagnostic hypothesis generation and human judgment. *Psychological Review*, *115*, 155–185.
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*, 297–323.
Wallsten, T. S., & Barton, C. (1982). Processing probabilistic multidimensional information for decisions. *Journal of Experimental Psychology — Learning Memory and Cognition*, *8*, 361–384.
Zsambok, C. A., & Klein, G. (Eds.). (1997). *Naturalistic decision making*. Mahwah, NJ: Elsevier.