Anticipation in cybernetic systems: A case against mindless anti-representationalism*

Lambert Schomaker
AI Institute / Groningen University
Groningen, The Netherlands
schomaker@ai.rug.nl

Abstract – *The developments in behavior-based robotics and in ecological psychology have had a strong effect on theoretical development in some research communities. A new belief has emerged under the name of anti-representationalism, which is strongly opposed to the notion of representations in cognition. This notion is spurred by the inarguably fruitful insight that behavioral complexity can be brought about by simple mechanisms at a low systemic level. Although there are many problems with constructed formal representations in the toy models of traditional artificial intelligence, there is a fundamental problem with extreme anti-representationalism, as well. Representations actually do exist in the biological neural-information processing system. In this paper, a review of neural representation mechanisms will be given, looking at perception and motor control in biological systems. Subsequently, it will be illustrated that already in simple animal behaviors, simple 'representation-less' reactivity does not suffice. Anticipation exists even in jumping spiders, requiring the existence of a representation as the computational basis for the prediction of future system states.*

Keywords: Representations in cognition, ecological theories of cognition, anti-representationalism

1 Introduction

Over the last decade, a new theoretical line of thinking has evolved in the fields of cognitive science, robotics research and biology. The work of Brooks [4] in robotics, Braitenberg's [3] revival of the ideas of Grey Walter [14, 15] on emergent complexity in behavior and the work of ecological psychologists Gibson [10] and Kelso [23] have provided its basis. A new belief has emerged under the name of anti-representationalism, which is strongly opposed to the notion of representations in cognition [17, 22]. Partly, this development is spurred by the very fruitful insight that some forms of behavioral complexity can be brought about by simple mechanisms at a low systemic level, taking into account embodiedness of the organism and its embeddedness in an (ecological) context. Although we do not really know what representations are, and although it

is probably a good thing to be skeptical of the constructed representations in some toy models of cognitive science and traditional artificial intelligence, there is a fundamental problem with extreme anti-representationalism. In the context of the current paper, to represent the external world means to *present* this external world *again*, internally within a cognitive system, in an adopted form from its physical projections which is however sufficiently informative for the organism to allow for selection, preparation and control of behaviors which are conducive to survival in its ecological niche.

It should be noted, for the sake of argument, that contrary to [13], it is assumed here that a given dynamical-system parametrization (e.g., an instance of Watt's governor) actually *does* represent aspects of its environment, while functioning. The difference between a biological control system and an engineered negative-feedback device such as Watt's governor is that the parameters of the biological control system are autonomously tuned during organism-world interaction. No matter what type of dynamical system is being implemented, the essence is that the parametric details are being tuned by a complex neural apparatus itself, just like the newly-born foal which quickly learns to stand upright against gravity.

Biological beings are not composed of a limited set of well-designed mechanical governors, they are composed of an enabling complex bio-chemical and physiological substrate that allows to learn to behave according to a set of differential equations, if and when that is required for survival or the performance of a playful complex motor task (cf. juggling in humans [1]). For both systems, engineered and biological, the representation will disappear if the system is isolated structurally and functionally from its operating context. Furthermore, the often-quoted example of Watt's governor constitutes a very unfortunate example in the discussion, since it concerns an engineered artifact representing an abstraction (a control field) par excellence and is the result of deep cognitive efforts and experimentation on the part of its designer. As such, Watt's governor is diametrically opposed to a genotypically and phenotypically emerged biologically instance of dynamical system control.

From a scientific viewpoint, the strongest objection originates from the realization that anti-representationalism, just as its ancestor "dynamic-systems theory" is opposed to the regular reductionist analysis of system structure and behavioral process. It has been the tremendously important contribution of cybernetics to science that it allowed for the detailed modeling of a system architecture and the transfer functions of the involved components. This is opposed to holistic modeling, e.g., by means of 'global attractors', as is promoted by advocates of dynamic-systems theory, exempt from an accompanying and healthy reductionist curiosity for underlying mechanisms at physiological, biomechanical and contextual levels.

Macroscopic modeling is useful, probably it is even necessary, but it can never replace the fundamental understanding of complex systems which emerges from detailed knowledge on the substrate and its information-processing abilities. What is more, macroscopic modeling can also be performed without grandiose anti-representational claims, by merely focusing on the essential aspects of macroscopic behavior and using rule-based modeling [12, 19]. However, the apparent attraction of the anti-representational perspective constitutes an oddity, in light of the tremendous evidence on a plethora of representational solutions in the biological nervous system.

In this paper, a review of neural representation mechanisms will be given, looking at perception and motor control in biological systems. The example of the jumping spider will be used to illustrate that already in simple animal behaviors, pursuit and prey catching simple 'representationless' reactivity does not suffice. In fact, all forms of anticipation require some form of representation as the computational basis for the prediction of future system states.

2 Symbolic representationalism

The idea that all information processing in intelligent autonomous systems can be reduced to the triggering of simple and isolated "reactive behaviors" for which no computational hidden state is necessary, is indeed appealing at first sight.

At the peak of the traditional symbolic paradigm of cognitive science and artificial intelligence in the middle 1980s there was a strong conviction that the sensory patterns which reveal aspects of the complex physical world had to be transformed into abstract symbolic entities as soon as possible in intelligent information processing. In computer vision, for example, it was believed -and sometimes still is- that in order to perceive an object such as a cube, the perceiver must have an internal and general three-dimensional (e.g. wire-frame) model of cubes, in order to solve the problem that the bottom-up information coming from both retinas does not describe the object completely. Explicit modeling was considered the starting point for any form of intelligence, following Immanuel Kant's synthesizing (top-down) approach to perception and cognition [1]. In robot vision and navigation, for instance, this approach implied that many details of the environment needed to be represented in a 3-D model. The notion of internal model or representation is appealing in many ways and can occasionally be exploited in working systems. However, several serious problems emerged with working models based on symbolic formalisms:

a) World models needed to be handcrafted painstakingly since autonomous learning of the world was considered too difficult;

b) Models were never complete;

c) Models were never completely correct;

c) Systems appeared to be rather weak in handling real-life problems.

Indeed, computer vision, speech and handwriting recognition appeared to constitute extremely difficult problems as opposed to artificial and constrained problems (computer chess). Additionally, the handcrafted origin of representations in symbolic models should be a source of skepticism, indeed. Different modelers utilize vastly different ways of modeling aspects of the world, and no principled way has emerged to arrive at models of the world which help an autonomous system-by-proxy to survive in a complex world under variable task demands. If a symbolic modeler starts out to mimic a process, it is likely that some working system will emerge at the end of the research project, but it is difficult to determine whether general applicability can be guaranteed. Today, we know that many properties of the physical world and of seemingly intelligent agent behavior can be modeled in a descriptive and at the same time effective manner, such as is realized, e.g., in computer games or in dialog systems. However, such examples are concerned with highly constrained conditions and well-defined contexts. Usually, if such systems are confronted with an open world containing unseen conditions, their response will become erratic.

3 Connectionist representationalism

In reaction to the shortcomings in handcrafted symbolic modeling, the tools which were developed in neural-network research [25, 2] solved a number of practical problems along the paths from perception to cognition and from cognition to effector control. Instead of handcrafting particular representations, it became convenient to utilize learning, i.e., parameter adaptation, to solve many of the problems that were hampering progress in traditional Artificial Intelligence research. In hindsight, the modeling tools of connectionism are just a subset of (implicitly) statistical methods. Also in this general class are the Bayesian and hidden-Markov

---

[1]A popular quote is: "there is no perception without prior knowledge and abilities", which cannot be found verbatim in *Kritik der reinen Vernunft (1781)*: Kant was much more subtle, leaving a role for empirical experience.

models, where explicit statistical modeling takes place. Two types of neural-network (NN) modeling can be identified.

In the first type of modeling, the property of learning of connectionist methods is exploited to solve hitherto difficult problems in pattern classification. This area of application-oriented research, has been very fruitful. As an example, multi-layer perceptrons can be found in many technological applications, today. The availability of multi-layer perceptrons now allows for a distillation and refinement process, extracting logical propositions (symbols) from complex sub-symbolic sensor-activation patterns. Once a neural network has derived a Shannonian bit from the sensor array, that output can be fed conveniently to a traditional symbolic-reasoning process. From a practical point of view, the NN approach alleviated the brittleness problem of symbolic AI in real-life applications to a very large extent.

A second subfield of neural-networks research concerns connectionist modeling of perceptual, cognitive and motor functions. This field of research attracted mainly cognitive psychologists who focus on the modeling of cognitive phenomena known from experimental psychology. Here, highly intricate neurally-inspired models are developed which aimed more at fitting experimental data than truly displaying the target cognitive functionality at a believable scale. Relevant examples are the McClelland & Rumelhart [25] interactive activation model of reading, the Elman [6] model of word-sense learning and the work of Seidenberg [16].

In any case, the fundamental breakthrough which was brought about by the neural-network modeling wave is the insight that there are many ways to represent information in local or distributed neuronal activation patterns. Non-linear function approximation by means of polynomials or Fourier analysis had existed before, but neural-network modeling did force researchers to think more precisely about connectivity and architecture in relation to the formation of representations. The connectionist notion of representation is in many ways less problematic than is symbolic representationalism: (a) learning is an intrinsic aspect of neural-network modeling; (b) the gap between model and biological system is still large but considerably narrower than is the case in symbolic modeling.

However, the design space of an artificial neural-network model is huge. It is necessary to constrain the models to a larger degree than is possible on the basis of the amount of empirical training data alone. Additional constraints are needed which may, e.g., be derived from the original biological neural architecture, as will be illustrated in the next section.

At this point, it is important to note that the discontent of anti-representationalists with the status of affairs in cognitive science and artificial intelligence is completely understandable. Rather than saving the world from arbitrarily handcrafted representations, neural-network research put us back in the same ballpark as the symbolic systems research, i.e., the ballpark of extensive tinkering and handcrafting. At the same time, however, it is also increasingly clear that throwing away the concept of *representation* may be similar to throwing the baby with the bathing water. Apart from being autonomously learnable, as neural-network research has shown, representations are also actually abundant in biological neural systems.

4 Biological neural representations

In this section we will give a brief overview on neural representations, i.e., neural architectures and processes that have evolved to represent physical variables at the input or output. To represent the external world means, in this context, to *present* this external world *again*, internally, in a slightly different form from its physical projections which is sufficient for the organism to select, prepare and produce the behaviors which are conducive to survival.

The parameters of the control functions in a living organism will be strongly determined by the physical properties of its ecological niche. Body mass, muscle strength, sensory modalities and their acuity all will have evolved to support survival, given the type of food, the type of shelter and the modes of transport which are typical of the given ecological niche.

A number of general neural representational mechanisms exist:

- Topological coding: Firing of a particular cell at a particular location in the tissue represents an important aspect of the current state (examples: vision, hearing, tactile sensing)

- Firing rate: (spikes/s) representing a physical signal (e.g., in motor control) or representing the likelihood of an observed feature (perception)

- Recruitment: the number of active neurons represents a quantity (e.g., force in motor control)

- Distributed representations and coherence: multimodality and information fusion

- Temporal coding, vetoing, synchronisation: low-level gating mechanisms

The concrete examples of representations which will first be given are located in peripheral sensory-motor information processing. However, it will be noted at the end of this section that neural representations of intermediate (central) processing stages are (a) unlikely to be absent and are (b) unlikely to differ substantially from the mechanisms which are used by the neural substrate in the processing of sensory-motor information.

4.1 Visual sensing

Light enters the eye and is projected onto the retina, a random raster of sensors for luminance and color. The central part of the projection is captured (i.e., represented) in high spatial resolution but low temporal resolution.

The peripheral visual field, on the contrary, is represented as a low-resolution signal, however, with high temporal resolution. Rather than being a passive full-field camera projection of the environment, the visual information is sensed by sequences of head and eye movements in most animals, such that the integrated (combined) visual information over a time window contains the essential elements of the outside world which are relevant to the species at hand. Extensive spatial and temporal preprocessing takes place, already within the eyes [18]. A stylized log-polar modeling of the retinal projection is sometimes used in robotics [28]. Figure 1 shows a schematic picture of this common biological representation for visual sensing.
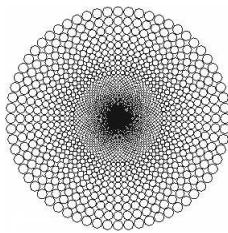
Figure 1: Schematic retinal layout[28], showing high central spatial resolution and reduced peripheral resolution.

4.2 Auditory sensing

Acoustic waves impinge on the mechanical parts of the hearing system and are transfered onto the basilar membrane, a structure containing vibration-sensitive hair cells. The auditory system in many animals realizes a representation of the complete necessary frequency spectrum through a combination of three encodings: (1) tonotopic place coding (Fig. 2) of spectral energy, (2) direct neural firing frequencies which match sound frequencies in a simple harmonic relation, (3) phase or volley encoding, where the sum of a number of low-frequency spike trains represents a high-frequency audio signal, made possible through fixed delays. The joint information of the three coding schemes yields a homogeneous and clear acoustical percept which spans 20Hz to 20 kHz, notwithstanding the considerable differences in the constituting neural encodings.
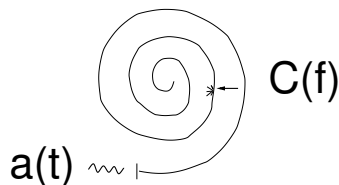
Figure 2: Tonotopic representation of sound on the basilar membrane. Air-pressure variations $a(t)$ yield an approximate spectral representation $C(f)$.
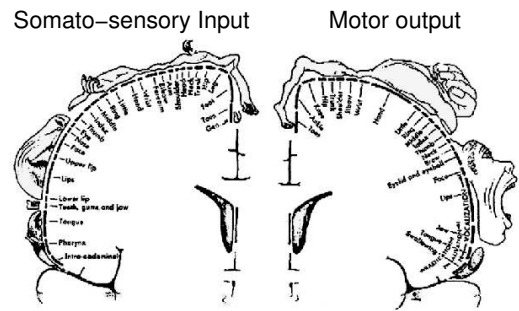

Figure 3: Input and output representations in the area for movement control, which covers two strips over the full width of the central cortex of each human brain hemisphere. The somato-sensory strip, representing tactile and proprioceptive input, which is located posterior to the central sulcus, is depicted on the left. The motor output strip, which is located anterior of the central sulcus, is depicted on the right. Both strips thus address a single half of the body. A morphed human-like 'homunculus' can be discerned, illustrating the topological representation of the body's skin and muscle tissues (after Penfield & Rasmussen [27]).

4.3 Tactile sensing and propriocepsis

The somatosensory post-central cortex picks up a morphed version of the tactile sensing pattern in the skin: the well-known homunculus projection of Penfield [27]. Propriocepsis allows for an inference of body and limb orientations by integrating length-difference signals coming from muscle-spindle sensors all over the body. The gamma-efferent system [24] is used for top-down feed-forward fine tuning of the sensitivity of the proprioceptive sensors (muscle spindles) to muscle-length variations on the basis of expected and imminent motor-task demands. Figure 3 shows the topological representation for this somato-sensory input, as well as for its counterpart, motor output.

4.4 Spatial orientation

In many animals, a vestibular system allows for the recording of head orientation changes along the three Cartesian axes. Apparently the biological system has evolved into an architecture that represents complex motion parsimoniously in an almost 3-D Cartesian fashion. Here, evolution has effectively carried out principal-components analysis (PCA), converging on a frugal three-dimensional representation of angular acceleration and therefore angular velocity and orientation of the head (Figure 4). Additionally and separately within the vestibular system, the gravity vector is represented by the otolithic subsystem in the following manner: Calcium carbonate pebbles (otoconia) are present on a layer of sensitive hair cells in an endolymph filled cavity which is part of the vestibular system. Gravity will make sure that the density of otoconia and the force exerted by those is largest in the spot which represents the gravity vector best. Neighboring hair cells cooperate in

improving the signal-to-noise ratio. Note that the biological system is re-utilizing the basic trick of sensitive hair cells located in an endolymph cavity three times, i.e., in acoustic, orientational and gravitational sensing.
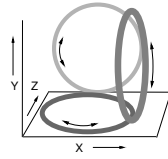

Figure 4: Schematic layout of vestibular system. A hair cell-based sensor in each of the rings detects head rotation, for each of the three Cartesian orientation axes (existing long before Descartes). This system effectively *represents* physical motion.

4.5 Motor control

All animals which make use of the muscle as the effector for navigation, object manipulation, attack/defense and mating will have to solve one very basic problem: muscles constitute an intrinsically non-linear component in the control system. On the basis of a single neural action potential, a group of muscle fibers will contract briefly and relax, yielding a single motor-unit twitch. Muscular contractility is up to 50%, energy expenditure is limited and the amount of force that can be delivered is considerable, such that this evolutionary product provided an attractive solution, at the cost however, of needing a complex control system.
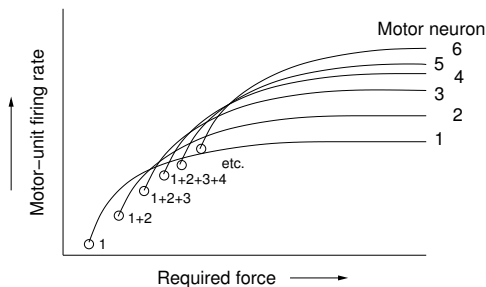

Figure 5: Required force is realized by firing-rate variation and recruitment of motor neurons. This representation scheme fulfills the requirement of both fine and coarse force control, given that motor units only produce brief all-or-none twitches.

The control problems can be enumerated as follows: (a) neural delay between motor neuron and end plate, (b) neuro-mechanical delay between arrival of the neural action potential at the end plate and the peak of mechanical force buildup and thirdly (c) the non-linearity of the muscle-fiber twitch, which can be modeled as an over-damped second-order function. The motor system is able to represent the required force and/or muscle-length ratios through two mechanisms: (1) firing rate control and (2) recruitment (Fig. 5). The first mechanism dictates that for a required pattern of small-force variations, a motor-unit pool is able to generate the necessary force by adapting the motor-unit firing frequency. However, there is an asymptote in the maximum force per motor unit. This problem is solved by the second mechanism, i.e., recruitment and de-recruitment. Motor-units are activated on demand. The total muscular output thus is a function of a weighted sum of twitch trains for the active motor units and of their firing rates. The stochastic spike pattern and the visco-elastic properties of muscle tissue guarantee smooth control.

4.6 Central neural representations

Between sensors and muscles, a number of neural pathways can be traveled, potentially passing neurons and axons whose activation may represent abstract pieces of information concerning the external world. The amount of examples in this domain is increasing quickly, due to better electrode technology and search methods which are guided by brain imaging techniques. Therefore, an exhaustive overview cannot be given here.

In navigation it has long been known that the activity of an individual neuron may be coupled to an absolute location in the world, after learning. These *place cells* [26] are located in the old brain (hippocampus) and are demonstrated in rats and squirrel monkeys. A place cell fires only if the animal is at a particular location in its cage. After getting acquainted to another environment, the new mapping will be unique but different. Apparently the place cells represent conjoint stimulus configurations which are characteristic of a location in the environment.

The second example concerns the *mirror neuron* system, which is involved in the recognition of body movements of conspecifics and non-conspecifics. Such neurons, which are at the premotor and parietal side of the brain in humans, will fire if a particular movement is observed, without actually activating the corresponding muscles in the observer. The map follows Penfield [27], i.e., a mirror neuron in the foot area will react if a moving foot is observed, etc. Computing such correspondences between retinal images and the motor map of the observer is far from trivial. Apart from a visual resonance between observed and known gestures, also acoustical associations may trigger mirror-neuron activity (cf., sound of a tapping foot).

The third example of an abstract representation concerns the invasion of ego-centric space as detected by neurons in the medial intraparietal area in some primates [5]. As soon as an arbitrary object becomes within reach of the arm, such neurons will fire.

The final example shows that abstract aspects of control are split at an early stage in image processing. There exists a distinction between the *where* and the *what* pathways, both addressing relevant but different aspects contained in the

sensory-visual information stream [11].

4.7 Representations galore!

Considering the topic of *representation* at this point, it appears to be counterproductive to maintain a rigid anti-representationalist stance in view of the richness and pin-pointed effectivity of the neural representations, the details of which are becoming increasingly clear. Only if dynamic-systems modeling and anti-representational approaches will yield predictions which can be confirmed at the low levels of the neural substrate, the value of this stance will be widely recognized. For now, we will precise the argument, noting that even in relatively simple animals, such as the jumping spiders (Salticidae), the notion of representation cannot be missed.

5   Anticipation and Representation

As noted before, the use of the muscle as an effector system poses important constraints on the controlling system. The delays which are involved in muscle activation necessitate the presence of a predictive functionality. In animals with a long spine, this situation is exacerbated by the cortico-muscular delay line (and its reverse proprioceptive connections). Therefore, most non-reflexive movements need to be planned ahead in time, as the environment and the objects contained in it will also be time variant. In primates, the frontal lobe of the brain has evolved as an extension of the predictive components of the motor and pre-motor areas, allowing for future-related computation. However, even in a relatively simple creature such as the jumping spider, its behavior can only be understood by assuming the presence of state-preservation as a representational mechanism to compute parameter settings for future system states. First we will deal with the question why it is *anticipation* in particular that calls for representation. Assume an acting (control) system with a non-linear transfer function $f(.)$, producing activity a in time, as a function of perceptual input x and of its internal parameters ω. Given this basic description (Eq. 1), a number of systems can be described differing in their use of the temporal context of x and a (Eqs. 2-5):

$$a_t = f(x_t, \omega) \tag{1}$$

$$a_t = f(x_{[t-T,t]}, \omega) \tag{2}$$

$$a_t = f(x_{[t-T,t]}, a_{[t-T,t-dt]}, \omega) \tag{3}$$

$$a_t = f(x_{[t-T,t]}, a_{[t-T,t-dt]}, \tilde{x}_{[t+dt,t+T]}, \omega) \tag{4}$$

$$a_t = f(x_{[t-T,t]}, a_{[t-T,t-dt]}, \tilde{x}_{[t+dt,t+T]}, \tilde{a}_{[t+dt,t+T]}, \omega) \tag{5}$$

where $dt \to 0$ and interval T is the same in case of past and future, for convenience. Eq. 1 concerns a system with a state-less, static transfer function. In Eq. 2, a system is described whose output a_t at time t can be known if its perceptual history $x_{[t-T,t]}$ in interval T is known, in other words, a non-linear finite-impulse response (FIR) system. A large class of systems can be described already, but the model is not suitable for systems whose previous output states influence the next output. Therefore, Eq. 3 introduces a system which needs a window of perceptual input and of previous action, yielding a non-linear combined finite + infinite (FIR+IIR)

impulse response. In the case of intrinsic delays, the systems described hitherto will fail in stable control, because corrective actions will always occur too late, as already noted by Wiener, in the case of guided-missile design. Therefore, it will be conducive if a control system can compute an estimate of expected future perceptual states $\tilde{x}_{[t+dt,t+T]}$ (Eq. 4). Finally, and most advanced, Eq. 5 describes a system which not only takes into account perceptual-motor history and expected perceptual input, but also its expected action state over a time window in the future. With the introduction of signals for expected future perceptual and action states, something interesting happens for realizable causal systems. Whereas information on past states can easily be represented by inertial properties of a (bio)physical substrate, a predictive system will need to set aside internal 'slots' for the computation and storage of estimated future states. In systems with anticipatory cognitive abilities, anti-representationalism becomes untenable.

Similarly, on a larger time scale, the learning function $\lambda(.)$ of system parameters ω can be categorized into a number of possibilities, depending on their usage of temporal context, introducing s for hidden internal states:

$$\omega_t = \lambda(x_{[t-T,t]}, \omega_{t-dt}) \tag{6}$$

$$\omega_t = \lambda(x_{[t-T,t]}, a_{[t-T,t-dt]}, \omega_{t-dt}) \tag{7}$$

$$\omega_t = \lambda(x_{[t-T,t]}, s_{[t-T,t-dt]}, \omega_{t-dt}) \tag{8}$$

$$\omega_t = \lambda(x_{[t-T,t]}, a_{[t-T,t-dt]}, s_{[t-T,t+dt]}, \omega_{t-dt}) \tag{9}$$

$$\omega_t = \lambda(x_{[t-T,t]}, a_{[t-T,t-dt]}, \tilde{a}_{[t,t+T]}, \omega_{t-dt}) \tag{10}$$

Examples of these learning approaches are as follows: Eq. 6 would encompass regular static multi-layer perceptrons; Eq. 7 concerns, e.g., recurrent Jordan multi-layer perceptrons; Eq. 8 concerns, e.g., recurrent Elman multi-layer perceptrons using the internal state s; Eq. 9, interestingly, shows the possibility of systems learning from their own estimates of future output (which may be very useful but is likely to be unstable). The most important conclusion at this point is that some form of state preservation, specifically dedicated to predicting future states will be needed as an internal representation for anticipatory control.

5.1   The jumping spider

The jumping spiders (Salticidae) are able to pursue a prey but also to jump onto a moving prey in order to catch it. This is an impressive feat for such an animal. Salticidae are equipped with an excellent visual apparatus, consisting of four eyes. The head is rigid, but the principal binocular pair of eyes can be moved to keep the image of prey centered on the retina. The parameters which can be derived from this feedback process can be used in continuous tracking (pursuit) but also in the computations which are needed for a jump with the intention to catch the prey. Salticidae have a multilayered retina with color vision. It is possible that the chromatic aberration is used for depth perception. The brain
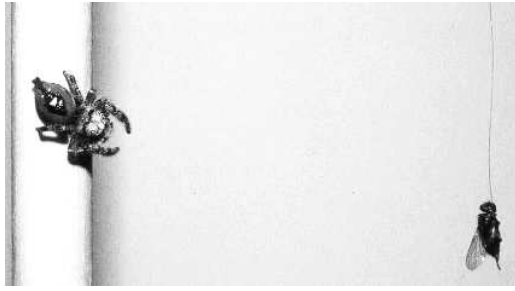
Figure 6: A photograph of a jumping spider (Phidippus pulcherrimus). The lure can be a housefly on a thread [20] or a black ellipse on the inside of a rotating cylinder [8]. Photographs kindly provided by dr. D.E. Hill

Figure 7: A stroboscopic photograph of a downward spider jump towards a lure [20]. Apart from aiming at the target position, the legs perform a grasping movement.

of a jumping spider includes a comparatively large region for visual processing. The principal eyes have a set of six muscles each for prey-image foveation. Salticidae may hunt other spiders, using mimicry and trial-and-error learning [29] to choose an appropriate signal for tampering with the web of a particular prey spider. Salticidae are able to make detours which involve evaluation of a situation, planning ahead to execute a pathway which may take it initially out of sight of the prey spider, then executing the detour, using a cognitive map [29]. Such skills place this animal among the top ranks in invertebrate cognition. However, we only need to concentrate on its ability to jump onto a moving prey to illustrate that intermediate representations are needed, even in relatively simple animals. Although a jumping spider can jump more than fifty times its body length, none of its legs has enlarged muscles: Apart from the exoskeletal leg-muscle contraction, it is assumed that a phasic contraction of muscles in the front part of the body increases the blood pressure in the exoskeleton, which causes the legs to extend rapidly. The effective control of this bi-modal motor system will require accurate and correctly timed neural excitation. The jumping spider is able to pursue prey efficiently by predicting its trajectory upto several seconds [8, 9]. Although pursuit will most probably involve the computation of first-order temporal differences which requires an internal state representation containing a slightly earlier perceptual-motor state, the context is one of closed-loop feedback with delays. To many researchers in dynamics-systems theory, this state of affairs would not be interpreted as entailing representations. However, the most interesting phase of the hunt concerns the final jump, which must be completely prepared. In a pro-active, feed-forward manner the parametrization of contractions in the bi-modal muscular system needs to be realized, taking into consideration the ballistics and aerodynamics of ego flight, in order to succeed in the catch at a predicted position of the moving prey. Figures 6 and 7 show photographs of two jumping spiders, one before and during a jump towards a (stationary) lure. Figure 8 depicts schematically the order of the involved processes in a jump towards a

moving prey. It is important to note that the essence of the argument presented in this paper concerns the fact that *the spider is planning a jump towards a position in space where there is no prey, as yet*. This planning implies an extraction of prey-trajectory parameters, transforming those into a parametric representation of muscular control, taking into account flight ballistics after lift off. It is assumed that the necessary computation can be derived from the prey-tracking eye movements. Such complex pro-active behavior requires intermediate representations to solve the involved differential equations and can hardly be compared to the purely reactive collision avoidance in Braitenberg [3] vehicles using linear feedback without the necessity for representation.
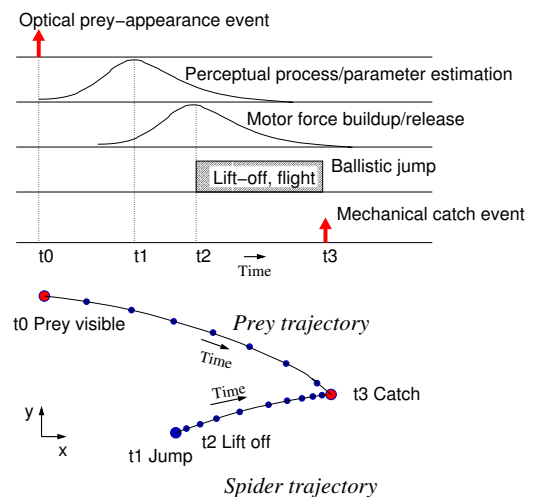

Figure 8: A schema of processes in the spider's jump & catch. The time functions at the top depict sequential order rather than time scale (the time axis is arbitrary). The bottom part of the figure shows the possible corresponding trajectories for prey and spider, from time of entering the visual field to the catch.

6 Conclusions

In order to apply simple rules, one may need complex systems and representations. The case of the jumping spider which is hunting for a moving prey and catches it through a ballistic jump shows that already in 'simple' animals, there are forms of behavior which are not purely reactive (i.e., non Brooksian) but pro-active, depending on estimates of future states of the world which cannot be realized in a simple linear manner. The control of the effector system and its ensuing flight are by no means a trivial implementation of a "time-to-contact" variant. The fact that learning[29] plays an important role in this species is an extra support for the notion that we do not deal with hardwired representationlessness, even in this creature. Finally, within the context of the theme (i.e., cybernetics), it is interesting to point out that control systems which have to solve a steering task in finite time $t = [0, T]$ are very well described in literature. The jumping spider effectively solves a Bolzano problem, a control-problem which can be modeled on the basis of Pontryagin's Maximum Principle, yielding the necessary steering functions if a penalty function is given [21].

As regards the use of pro-active control in the robots, we are currently experimenting with a trajectory-control mechanism in typical "Robocup"-type Pioneer-II robots, which is based on the ballistic jump, however in the two-dimensional plane. For safety reasons, the control signal for this catching behavior will be superimposed on the regular ultra-sonic collision avoidance behavior. The idea is to accept the risk of missing a target, but effectively increasing the speed of field exploration if salient features are detected, by means of series of 'jumps'. It is expected that such behaviour will be much more akin to purposive natural navigation than the moth-like meandering which is so typical of the real representation-less Braitenberg vehicles which can be observed in many robot competitions. Rather than hunting flies, our models will be directed at collection colored balls in the environment, or hunt for legible text patterns in a human-made environment.

References

[1] P. J. Beek. "Juggling dynamics". *Doctoral dissertation*. Free University Press, Amsterdam, 1989.

[2] C. M. Bishop. "Neural Networks for Pattern recognition." Oxford University Press, Oxford, 1995.

[3] V. Braitenberg, *Vehicles: Experiments in Synthetic Psychology*, MIT Press, Cambridge, MA, USA, 1984.

[4] R. A. Brooks, "Intelligence without representation", *AI Journal*, Vol 47, pp. 139-159.

[5] C. L. Colby & M. E. Goldberg. "Space and attention in parietal cortex." *Annual Review of Neuroscience*, Vol 22, 1999.

[6] J. L. Elman. "Finding structure in time". *Cognitive Science*, Vol 14, pp. 179-211, 1990.

[7] L. Fadiga, L. Fogassi, G. Pavesi & L. Rizzolatti. "Motor facilitation during action observation: a magnetic stimulation study". *J. of Neurophysiology*, Vol 73, pp.2608-2611, 2003.

[8] L. M. Forster. "Vision and prey-catching strategies in jumping spiders." *American Scientist*, Vol 70, pp. 165 175, 1982.

[9] L. M. Forster. "Visual mechanisms of hunting behaviour in jumping spiders (Araneae: Salticidae)." *N.Z. Journal Zool.*, Vol 4(4), pp. 6., 1979.

[10] J. J. Gibson, *The ecological approach to visual perception*, Hougton Miffin, Boston, USA, 1979.

[11] M. A. Goodale & A. D. Milner. "Separate pathways for perception and action". *Trends in neurosciences*. Vol 15(1), pp. 20-25, 1992.

[12] C. Gössmann, C. Hemelrijk, R. Huber, R. "The formation and maintenance of crayfish hierarchies: behavioral and self-organising properties." *Behavioral Ecology and Sociobiology*, Vol 48, pp. 418-428, 2000.

[13] T. van Gelder, T. "Revisiting the Dynamical Hypothesis." *Preprint No. 2/99*, University of Melbourne, Department of Philosophy, 1999.

[14] W. Grey Walter, *The Living Brain*, W.W. Norton & Company Inc., New York, 1963.

[15] W. Grey Walter, "An imitation of life", *Scientific American*, pp. 42-45, May 1950.

[16] M. Harm & M. S. Seidenberg. "Reading acquisition, phonology, and dyslexia: Insights from a connectionist model." *Psychological Review*, Vol 106, pp. 491-528, 1999.

[17] W. F. G. Haselager, A. D. de Groot & J.F.H. van Rappard, "Representationalism versus anti-representationalism: A debate for the sake of appearance", *Philosophical Psychology*, Vol 16(1), pp. 5-23, 2003.

[18] J. H. van Hateren, "Spatiotemporal Contrast Sensitivity of Early Vision", *Vision Research*, Vol 33, pp. 257-267, 1992.

[19] C. K. Hemelrijk. "Towards the integration of social dominance and spatial structure." *Animal Behaviour*, Vol 59, pp. 1035-1048, 2000.

[20] D. E. Hill. "Orientation by jumping spiders of the genus Phidippus (Araneae: Salticidae) during the pursuit of prey". *Behav. Ecol. Sociobiology*, Vol 6, pp. 301-322, 1979.

[21] S. Iyanaga & Y. Kawada, (Eds.). "Pontryagin's Maximum Principle." In *Encyclopedic Dictionary of Mathematics*. MIT Press, Cambridge, MA, pp. 295-296, 1980.

[22] F. Keijzer, *Representation and Behavior*, MIT Press, Cambridge MA, 2001.

[23] J. A. Scott Kelso. *Dynamic Patterns: the self-organization of brain and behavior*. MIT Press, Boston, 1995.

[24] S. W. Kuffler, C. C. Hunt & J. P. Quilliam. "Function of medullated small-nerve fibers in mammalian ventral roots; efferent muscle spindle innervation." *J. Neurophysiol.*, Vol 14, pp. 29-54, 1951.

[25] J. L. McClelland and D. E. Rumelhart. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition: Volume 1 Foundations*. MIT Press, Cambridge, MA, 1986.

[26] R. Muller. "A quarter of a century of place cells." *Neuron*, Vol 17(5), pp. 813-822, 1996.

[27] W. Penfield & T. Rasmussen. *The Cerebral Cortex of Man. A Clinical Study of Localization of Function*. The Macmillan Comp., New York, 1950.

[28] M. Tistarelli, G. Sandini, "On the Advantages of Polar and Log-polar Mapping for Direct Estimation of Time-to-Impact from Optical Flow". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol 14, pp. 401-410, 1993.

[29] S. Wilcox & R. R. Jackson. "Jumping spider tricksters: deceit, predation, and cognition". In: M.Beckoff, C. Allen and G. Burghardt (Eds.). *The cognitive animal*. MIT Press, Cambridge, MA, 2002.