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Interactions between Motivation, Emotion and Attention: From Biology to Robotics

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Abstract

A model of emotional conditioning is extended with a cortical model where stimulus codes compete for activation. This system is combined with motivational inputs that modulate both sensory and emotional processing. The extended model is able to reproduce the attentional blocking effect. It can also learn to switch between different sensory targets when the motivational state changes. The relation between motivation, emotion, and attention control is learned through the presentation of different stimuli in combination with reward. The model has also been used to control saccades in a stereo vision head that learns what object are compatible with what motivations.

1. Introduction

Although the importance of emotions (or value systems) have been stressed for autonomous systems (Huang and Weng, 2002; Canamero, 2003), it is seldom discussed in relation to stimulus selection. However, a robot with multiple goals and motives must be able to learn what objects are useful for each of its activities. This is even more important for a developing system where object representations and more complex motivations need not be present initially.

Stimulus selection can be carried out by assigning an emotional value to each stimulus depending on how well it satisfies each motivation. The development of this ability in children has only recently come into focus (Hajcak and Dennis, 2009), but it has been studied extensively in animals. The assigning of an emotional value to a stimulus is most likely controlled by classical conditioning and is believed to take place in the amygdala and related structures in the brain (Rolls, 1995; LeDoux, 1995). As a result of this learning, processing of motivationally significant stimuli is enhanced (Morris and Dolan, 2001).

Classical conditioning is often assumed to play a secondary role in the control of action, it can be sufficient on its own in situations where only a single action is needed (Balleine and Dickinson, 1998). For example, once the target stimulus has been selected, an innate appetitive system could be responsible for approaching the target and eventual consummation (Balkenius, 1995). In this case, all that is needed of the organism is that the correct target stimulus has been selected. It is also necessary to decide whether the target should be approach or not.

We have extended a computational model of the amygdala with two mechanisms that makes this possible. The first is a selection mechanisms that determines what stimuli should be allowed to remain active and the second is an approach system that is activates by the output from the amygdala. It is assumed that a stimulus that has been paired with reward is worth approaching. We have also added a mechanism that relates this choice as well as the emotional reactions to the current motivational state. Although a lot about the brain system for stimulus evaluation is not known, a number of computational models have been proposed and these can be used as a basis for a robot implementation of an emotional system.

The system level model is centered around the function of the amygdala which is a system of interrelated nuclei within the temporal lobe that is responsible for the conditioning of emotional reactions to previously neutral stimuli (Rolls, 1995; LeDoux, 1995). The extended amygdala is involved both appetitive (Waraczynski, 2006) and aversive (LeDoux, 1995) learning. The amygdala is not only involved in the generation of emotional reactions, it also plays a role in the modulation of different processes in other parts of the brain.

One effect of an emotional reaction in the amygdala may be to modify the cortical coding of emotionally charged stimuli Vuilleumier and Huang (2009). The size of the cortical code for a stimulus increases with repeated presentation to allow a larger set of cells in cortex to be tuned to the specific properties of the stimulus. This effect is enhanced if the presentation is combined with an emotional reaction. Weinberger (1995) has shown that the cortical area representing a stimulus increases in size when it takes part in emotional conditioning. This process is thought to be controlled by the back-projection from the amygdala to cortex through the nucleus basalis of Meynart (nbM) (Weinberger, 1995). Through these connections, the amygdala could modulate learning in the sensory system based on how emotional the current situation is (LeDoux, 1996) by non-specifically controlling the level of acetylcholin in cortex.

Another effect of amygdala activity could be to bias processing in cortex towards stimuli that have an emotional significance. In contrast to the projections from cortex to the amygdala, the direct back-projections from the amygdala to cortex influence the whole of sensory cortex (LeDoux, 1996). These projections could take part in emotional priming of sensory processing by enhancing processing (or attention) to stimuli that have emotional significance (Wilson and Rolls, 1990; Wilson and Ma, 2004). This type of emotional influence on cortical processing could lead to a form of biased competition (Desimone and Duncan, 1995) where emotionally relevant stimuli are able to suppress stimuli that are not of emotional significance. This mechanism could possibly explain how emotional reactions can influence attention (Jolkkonen et al., 2002). Unlike the modulation of learning, this type of feedback to cortex must be specific to particular cells in cortex that code fore the relevant aspects of the stimulus.

If emotional evaluation of stimuli influence activity in cortex, this modulation will subsequently also influence learning. A neutral stimulus that is presented together with an emotional stimulus may be suppressed and would not be able to form association with reward or punishment. This is the essence behind attentional theories of blocking (Kamin, 1968; Mackintosh, 1974; Grossberg, 1975).

The goal of the present system is to investigate how a computational architecture motivated by the interactions of different emotional and motivational structures in the brain can be used as a basis for a control system for a robot.

2. A System-Level Model

The emotion/motivation system described here is an extension of the model of the amygdala proposed by Balkenius and Morén (2000) and further developed by Morén (2002). This model is described at a system-level and is not intended to model the details within each component. Instead it aims at understanding the overall function of the system of interacting components. Here we add two important new components that drastically increase the scope of the model (Fig. 1). The first addition is the inclusion of a cortical model that allows for biased competition between cortical codes and makes attentional processing possible. The second addition is a motivational system that modulates emotional as well as sensory processing.

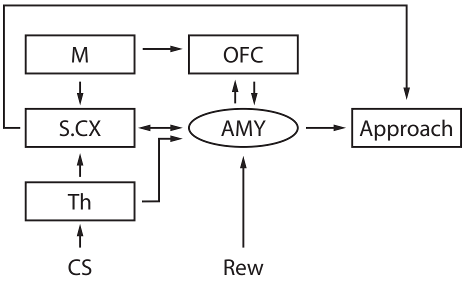

Figure 1: *Outline of the model. Th: thalamus, S.CX: sensory cortex, M: motivational state, AMY: amygdala, OFC: orbitofrontal cortex, Approach: approach system parameterized by the selected activity in S.CX. See text for explanation.*

The model consists of a number of components named after different brain regions. In the following subsections, these labels refer to parts of the model rather than their biological counterparts.

2.1 Cortex

The cortical subsystem must have two features that are critical to the operation of the system: First, it is necessary that multiple cortical codes can be simultaneously active. For example, if the robot is simultaneously looking at two different objects, it must be possible for them to activate two different set of codes in cortex. This is generally a feature of many neural network model of visual processing, but it excludes the direct use of models such as the standard self-organizing map that only allows a single activated region.

Second, the competition can be modulated by external signals. This idea was put forward by to explain attentional modulation of cortical codes (Duncan, 1998), but is also applicable to the emotional or motivational influence on cortex.

There are several ways to implement these ideas and here we have chosen the following. Let I_i be one input to cortex and let x_i be the corresponding cortical activity. To simplify the description, we assume here that one input component is directly responsible for the activation of one particular cortical code. The competition for activation is modeled in three steps. First x_i is set to the input I_I. Second, the current bias $B_i(t)$ is calculated as

$$B_i(t) = \beta + \sum_j m_j(t) b_{ji}(t) \tag{1}$$

where β is the bias when no motivational input is available. This makes sure that all inputs have a chance of activating cortex. Finally, the following recurrence relation is iterated until the values of x_i converge:

$$\xi_i(t) = [f(x_i(t)B_i(t) - \theta)]^+ \tag{2}$$

$$x_i(t+1) = \frac{\xi_i(t)}{\|\xi(t)\|} \tag{3}$$

where $f(x) = x^2$, θ is a threshold and $[x]^+$ indicates that the value of x must be zero or larger. As a result, the cortical activity will be normalized and activity levels that falls below the threshold will be removed.

2.2 Amygdala

The amygdala is modeled as an associator that connect its input vector to a single emotional output. This output can also be inhibited by the output from the orbitofrontal cortex. A complete description of the amygdala model can be found in (Morén, 2002). Here we only summarises the required equations without justification.

The output from the amygdala E is calculated as

$$E(t) = \left[\sum_i x_i(t)V_i(t) - E_O(t)\right]^+ \tag{4}$$

where I_i is the input from cortex and thalamus, E_O is the input from OFC, and V_i are connection weights that are updated according to

$$\delta V_i(t) = \alpha x_i(t-\tau)\left[R(t) - \sum_i I_i(t-\tau)\right]^+ \tag{5}$$

The reward (or US) is given by R and and α is the learning rate. The optimal inter-stimulus interval is given by τ.

2.3 Orbitofrontal Cortex

The orbitofrontal model receives as input the current cortical state and the current motivational state M and learns to inhibit and emotional reaction when it is not appropriate. As for the amygdala model, the full explanation and justification for the equations can be found in Morén (2002), but we include them here for completeness.

The output from the orbitofrontal cortex is given by

$$E_O(t) = \sum_{ij} T_{ij}(t) W_{ij}(t) \tag{6}$$

where $T_{ij} = x_i(t)M_j(t)$ and W_{ij} are the connection weights that are updated according to

$$\delta W_{ij}(t) = \beta T_{ij}(t-\tau) R_O(t) \tag{7}$$

The learning rate is set by β and R_O is the reward function. When $R \neq 0$, the reward is set to

$$R_O = \left[\sum_i x_i(t)V_i(t) - R\right]^+ - \sum_i T_{ij}(t)W_{ij}(t) \tag{8}$$

and otherwise the following equation is used

$$R_O = \left[\sum_i x_i(t)V_i(t) - \sum T_{ij}(t)W_{ij}(t)\right]^+ . \tag{9}$$

2.4 Motivational System

The motivational system is here modeled as a single vector M where the level of each component indicates the strength of the corresponding motivational state. We do not model the dynamics of the different motivations here and M can thus be seen as an input to the system.

2.5 Approach System

The approach system is based on the notion of attention as selection-for-action (Allport, 1990; Hannus et al., 2005). The approach system is assumed to lead the robot toward a stimulus either by locomotion or by reaching for it. Here, we leave it unspecified what exact approach mechanism is used as long as its actions can be parameterized based on the currently coded stimuli in the cortex.

It is possible that other learning mechanisms are used within the approach system to learn the sensory-motor transformations necessary to approach the target stimulus. The approach system can be seen as a part of a more general appetitive subsystem (See Balkenius 1995 for an overview).

The approach system has two inputs. The first is the cortical coding of the target stimulus that is used to direct the produced action. The second is the emotional output from the amygdala that activates the behavior itself. It is possible that the approach system produces a behavior directed at the stimulus currently in focus even without emotional activation, but it will be less vigorous and will habituate if it does not lead to a reward (Balkenius, 2000).

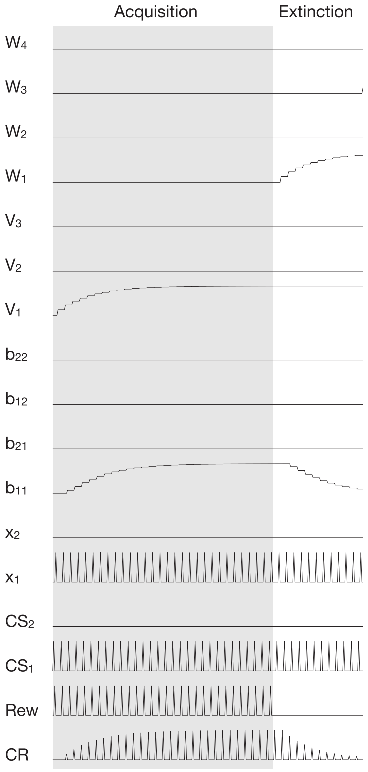

FIGURE 2: *Simulation of acquisition and extinction of a conditioned emotional response. The connections weights are shown in the lines marked with W_i and V_i, b_{ji} are the bias weights, x is the cortical activity, CS are the sensory inputs, Rew is the reward, and CR is the conditioned emotional response.*

3. Computer Simulations

In this section we show the results of a number of computer simulations of the complete system to illustrate its function in different situations. All simulations were run using the Ikaros system (Balkenius et al., 2009). Only two stimuli and two motivational states were used to simplify the results but all simulations can be extended with larger number of stimuli.

3.1 Stimulus Evaluation

This simulation shows how the model can learn which stimuli predict reward and how these predictions can change over time. This is an example of standard classical conditioning and extinction (Pavlov, 1927). The developments of the different values over time are shown in Fig. 2.

During the acquisition phase the stimulus CS_1 is paired with the reward (Rew) and as a result the associative weight V_1 increases and allows the stimulus to produce the conditioned emotional response CR. The motivational bias b_{11} also increases to enhance attention to the stimulus in cortex. During the extinction phase, the stimulus is presented on its own and as a result the inhibitory modulation from OFC (W_1) will increase an suppress the emotional response. At the same time, the motivational bias b_{11} will decrease again.

Note that after extinction, the emotional response is only inhibited by the current motivational state through orbitofrontal cortex. If the motivation changes, the behavior can thus reappear quickly which is what happen in animals when the extinction context changes (Bouton and Nelson, 1998; Morén, 2002).

The emotional reaction that is produced can be seen as an evaluation of the stimulus. A larger reaction indicates a more valuable stimulus which should be attended as closely as coded by the bias and approached as vigorously as coded by the CR which in turn will activate the approach system.

3.2 Attentional Blocking

Blocking is the well known phenomenon that a stimulus that is presented together with an already conditioned stimulus will not acquire an association with the reward (Kamin, 1968). This result was originally explained as a the result of attentional competition (Mackintosh, 1974), but has later mainly been explained as a competition for association with the reward (Rescorla and Wagner, 1972).

We simulated this phenomenon with the model as illustrated in Fig. 3. The system is assumed to be in motivational state 1. First CS_1 is presented together with the reward a number of times which leads to increases in V_1 and b_{11}. This is followed by the presentation of both CS_1 and CS_2 together with the the reward. As V_1 has already reached its asymptotic value, no learning occurs in this phase. Finally, CS_1 and CS_2 are individually tested and as can be seen only CS_1 produces an emotional response.

In addition to showing that the system reproduces the blocking phenomenon, the simulation also illustrates that the two theories of blocking are not mutually exclusive since the system incorporates both mechanisms. Attentional blocking is used to select emotionally relevant stimuli in cortex and competition for associative strength is used within the amygdala to limit the range of the learned associations. Attentional selection of this type is essential in more complex learning situation as illustrated by the next simulation.

3.3 Switching

This simulation demonstrates that the model will select a stimulus that has been paired with reward in the current motivational state when several stimuli are simultaneously present (Fig. 4). First the system is conditioned with CS_1 in motivational context M_1, then it is conditioned to CS_2 in motivation M_2.

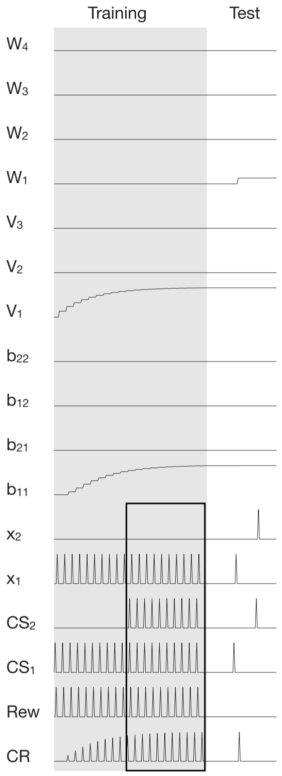

FIGURE 3: *Attentional blocking. The frame marks the compound conditioning trials that are followed by two tests with CS_1 and CS_2 respectively. Refer to Fig. 2 for an explanation of the different labels.*

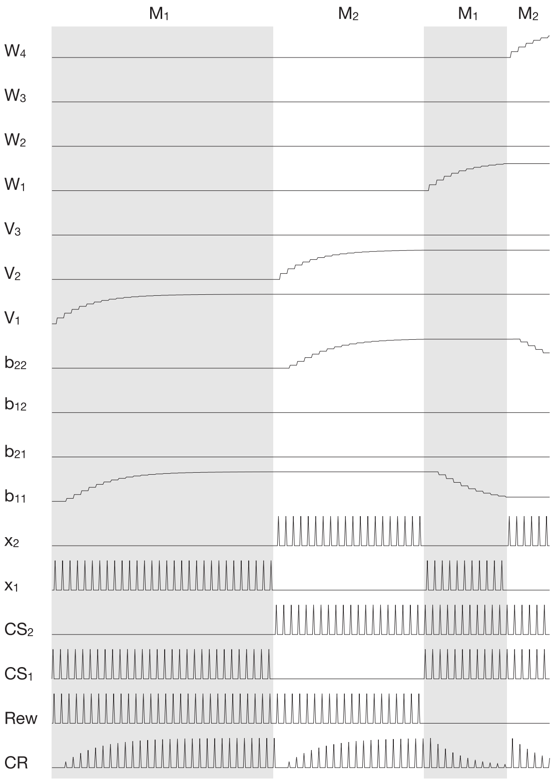

FIGURE 4: *Switching of attention as a function of motivational state. See Fig. 2 for an explanation of the different labels.*

Finally, the system is tested in motivational state M_1 with both stimuli. As can be seen in the figure, only the stimulus compatible with motivation 1, that is CS_1, is active in cortex. When the motivational state is subsequently switched to M_2, the cortical code also switches to activate stimulus CS_2 instead.

In this simulation, there is only a positive bias from the motivation on the cortical activity. The selection is the result of biased competition within cortex. The reason why W_1 and W_4 increases is that the associations undergo extinction during the final test phase.

We also tested a slightly more complicated situation where both stimuli were presented in both motivational contexts, but only rewarded in one (Fig. 5). There are four distinct training regimes that are repeated four times:

- $M_1 : CS_1 + Rew$
- $M_2 : CS_1$
- $M_1 : CS_2 + Rew$
- $M_2 : CS_2$

As a result, both stimuli undergo extinction in one motivational context. Finally, the system is tested in motivational state M_1 with both stimuli present. Initially, the system selects stimulus CS_1, but since it does not receive any reward, the emotional response CR gradually decreases. At the same time, the bias for CS_1 in M_1 decreases until the system is ready to try out CS_2 instead. At this point, the emotional response is very weak, but will be sufficient for the system to investigate CS_2 if there is no other stimulus present. Since CS_2 is not rewarded either, the system then alternates back to CS_1 a second time and then back to CS_2, before the emotional reaction is completely extinguished.

This simulation shows that the model can learn what stimulus satisfies which motivation also in situations with inhibition. The cortical competition is essential in this case since the inhibiting stimulus would otherwise have shut off the emotional reaction for the stimulus that was conditioned in the current motivational state.

4. A Robot Implementation

Preliminary tests have been performed with a stereo head that is controlled by the model described above (Fig. 6). The same code was used as in the simulations above except that the input and outputs were connected through a number of extra Ikaros modules

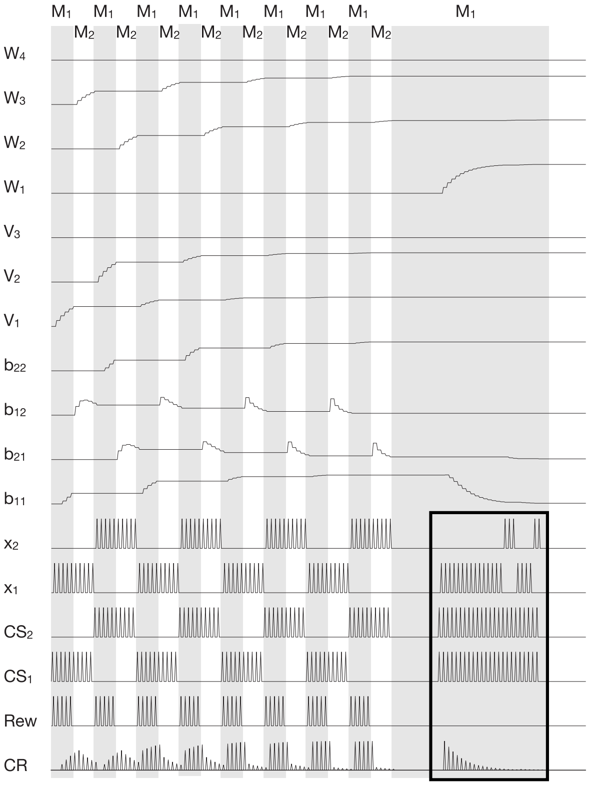

Figure 5: *Switching of attention after repeated acquisition and extinction in different motivational contexts. (See Fig. 2 for an explanation of the different labels.)*

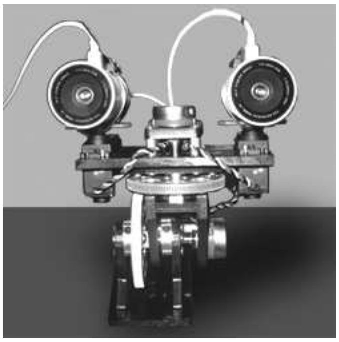

Figure 6: *A stereo head used to test the system with visual stimuli.*

to a robot head.

In addition, the two cortical nodes are replaced with a full saliency map where different features at different locations compete for activation. The implementation is based on the learning saliency map described by Balkenius et al. (2008), which in turn was inspired by the work of Itti and Koch (2001).

The saliency map is used to select the target stimulus which is then used as a parameter for the approach system which in this case is the saccade system that moves the gaze toward the selected stimulus. No other action is currently implemented.

In the tests, objects of two different colors were used as stimuli and the saliency map was trained exactly as in the switching simulation described above. The reward and motivational state was externally supplied and the reward was triggered by a saccade to the correct stimulus.

Apart from showing that the model can be used in a robot, this implementation also clearly illustrates the similarity between cortical competition, attentional blocking and saliency maps.

5. Discussion

The features of a motivational/emotional system that we have described above are essential in a robotic system that develops its cognitive abilities over time. As it encounters new objects in the environment or learn new skills, it needs to learn what actions and objects fit which motivations. We believe that the system-level model developed here contains several fundamental components of such a system. The model has a number of attractive properties. It is reasonably similar to the corresponding system in animals and it is computationally sound while incorporating a number of useful mechanisms. It bridges the gap between models of conditioning and models of attention control to allow classical learning mechanisms to control attention. It also suggests a way to incorporate modulation by the current motivational state on sensory and emotional processing.

The results are comparable to our earlier modeling of task-switching in instrumental learning (Balkenius and Winberg, 2004). The main difference is that there is only one action in this system and that cortical competition between different stimuli is necessary here while that is not the case in the instrumental situation. The model resembles the model proposed by Mannella et al. (2007) in that it includes interaction between motivational states and emotional responses, and learns to select behavior depending on the motivational state. The present model is different in that it attempts to explain the modulation of sensory processing rather than action selection.

There are a number of additional components that will need to be added for a more flexible and less specific learning ability. The components should work in close cooperation wit the subsystems described here. The approach system needs to habituate when no reward is received. A mechanism that can handle this was described by Balkenius (2000). It is also necessary to include instrumental learning to allows learning of flexible behavior sequences. Instrumental learning could also in principle be under motivational control in the same way as emotional learning although the situation is probably more complex in humans and animals (Balleine and Dickinson, 1998). Both instrumental and classical conditioning could additionally interact with habit systems that learns to produce behavior after repeated rehearsals.

There is also a need for adaptive sensory-motor mappings that learn goal-directed behavior that the other learning systems can activate or inhibit. One final feature that is missing in the present system is a mechanism that can handle incentive motivation (see Balkenius 1995). This is something that we want to add in the future.

We will also extend the robotic implementation of the system to include some form of manipulation and not only a head. The general structure of the control will be very similar to what we have now, except that the appetitive approach behavior will contain several segments such as visual fixation followed by reaching and possibly exploration or ingestion.

In summary, we have shown how a model of emotional conditioning can be extended with multiple motivations to learn what stimuli are rewarding in each motivational state. In addition, we have shown how the extended model can handle competition for attention in a cortical subsystem. Both these abilities are essential for a robot that is engaged in many different activities motivated by different goals or needs.

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