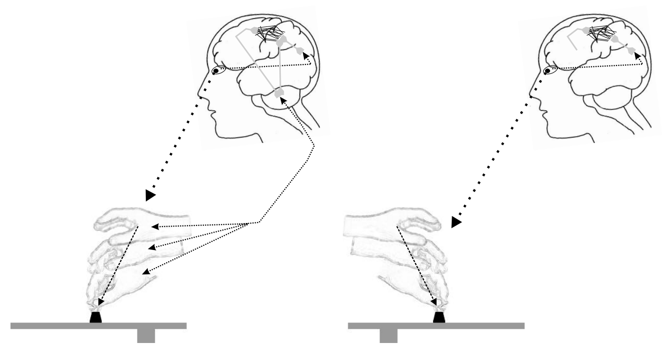
Bidirectional ARTMAP: An Artificial Mirror Neuron System

Martin V. Butz
Illinois Genetic Algorithms Laboratory (IlliGAL),
University of Illinois at Urbana-Champaign, IL 61801.
Phone: +1 217 333 2346, fax: +1 217 244 5705,
e-mail: butz@illigal.ge.uiuc.edu

Sylvian Ray
Department of Computer Science,
University of Illinois at Urbana-Champaign, IL 61801.
Phone: +1 217 333 0806, fax: +1 217 333 3501,
e-mail: ray@cs.uiuc.edu

***Abstract*— The recent detection of *mirror neurons* in monkeys suggests that brains encode parts of an observed action in a similar way they encode own actions. This paper models such a mirror system by means of adaptive resonance theory (ART) artificial neural networks coupling them in a manner similar to ARTMAP systems. Particularly, a bidirectional ARTMAP system (BiARTMAP) is created. The system associates executed actions with consequent action-effects. The associative structure gives the system mirror capabilities: On the one hand, perceived environmental changes cause an action association. On the other hand, activated action patterns cause the expectation of resulting environmental change. We also show that many other proposed cognitive processes relate to the BiARTMAP architecture. Future work includes the incorporation of situational dependencies, the combination of BiARTMAP with vector associative maps (VAMs), and the integration of BiARTMAP in a behavioral module enabling anticipatory behavior. Application wise, BiARTMAP can be applied as a general classifier and/or associative network.**



(a) Executing own action (b) Observing action

Fig. 1. Sketched mirror neuron activity in person doing an action or observing somebody else doing the same action.

I. Introduction

Mirror neurons are one of the major discoveries of recent Neuroscience research [1], [2]. The findings show that there are neurons in monkeys and most probably human brains that are active not only when performing a particular action, such as grasping an object, but also when observing another monkey/human performing the same action (cf. Figure 1). This shows that making sense of other people's actions is (at least partially) realized by the re-use of neuronal pathways that represent one's own actions.

More recently, suggestions emerged about the fundamental importance of this process. Arbib [3] proposed mirror neurons as a prerequisite for the evolution of language. He suggests that it may only be possible to comprehend other people's speech acts by simulating these acts with neurons identical to ones own speech acts. Somewhat similar, Gallese [4] relates mirror neurons to empathy. He argues that only due to mirror neurons it may be possible to become socially involved enabling understanding and prediction of other people's intentions.

While these suggestions need to be kept in mind for future research directions, this paper introduces a simple first approach of how such a mirror system might be modeled by means of artificial neural networks (ANNs). We use adaptive resonance theory (ART) [5], [6] ANNs. In particular, we extend the fuzzy ART [7] and fuzzy ARTMAP architectures [8], [9] to model mirror neurons. Functioning of the resulting fuzzy bidirectional ARTMAP system (BiARTMAP) is illustrated and evaluated in a blocks world problem. Further relations to cognitive processes suggested in psychology support the usefulness of BiARTMAP. Finally, future work directions stress the potential of the derived system.

II. Fuzzy bidirectional ARTMAP

Fuzzy bidirectional ARTMAP (BiARTMAP) modifies and enhances fuzzy ARTMAP. After the derivation of the system, we focus on interaction, learning, and mirror capabilities.

A. Fuzzy ART in a Nutshell

Adaptive resonance theory (ART) was originally proposed in [10], [11] and tested in [5]. ART systems are artificial neural networks which are capable of categorizing arbitrary sequences of unlabeled input patterns in real time. Thus, ART systems resemble a basic clustering algorithm in which *similar* input is represented by one category. The degree to which input can be similar is controlled by a *vigilance threshold*. If the similarity criterion is violated, a new category node is created that represents the current input.

More formally, input (such as a problem instance) $I = (I_1, ..., I_M)$ $(I_i \in [0, 1])$ is fed into the ART $F_1 = (x_1, ..., x_M)$ field as *bottom-up* input. The F_1 field also receives *top-down* input from the category field $F_2 = (y_1, ..., y_N)$. A weight vector w_{ji} is associated with each category y_j in F_2.

Initially, $w_{ji}(0) = 1$ and the categories of F_2 are said to be *uncommitted*. The weight vector subsumes both the top-down and bottom-up weight vectors of ART.

Fuzzy ART learning is controlled by three parameters: (1) the mentioned vigilance threshold $\rho \in [0, 1]$ controls resonance (or similarity), (2) the choice parameter $\alpha > 0$ influences choice priority, and (3) the learning rate β controls the speed of network adaptation.

Given an input I all categories j become active with activity $T_j(I)$:

$$T_j(I) = \frac{|I \wedge w_j|}{\alpha + |w_j|} \tag{1}$$

Hereby, operator $\wedge$ denotes the fuzzy operator (i.e. $a \wedge b = min(a, b)$), and the norm $|\cdot|$ is defined by $|a| = \sum_i |a_i|$.

According to the category activities, one category is chosen as being the active node J.

$$J = arg \max_{j \in 1,...,N} T_j(I) \tag{2}$$

This active node is then tested for resonance which depends on the degree to which I is a fuzzy subset of w_J. In particular, resonance occurs if the following vigilance criterion is met.

$$\frac{|I \wedge w_J|}{|I|} \geq \rho \tag{3}$$

If resonance does not occur, T_J is set to zero and the next best choice according to Equation 2 is tested for resonance. This *match tracking* continues until a category choice satisfies Equation 3. Note that this is always the case for an *uncommitted* node so that the search is assured to end. Once search ends, the weight vector w_J is updated according to the following equation.

$$w_J(new) = \beta(I \wedge w_J(old)) + (1 - \beta)w_J(old) \tag{4}$$

For fast learning in the beginning and then further adaptivity, β is set to one when the node is uncommitted, and it is set to a base value thereafter. *Complement Coding* is applied to normalize the data preserving amplitude information and assuring that for all inputs I, $|I^C| = M$. I^C is a 2M-dimensional vector $I^C = I_1, ..., I_M, I_1^C, ..., I_M^C$ where $I_i^C = (1 - I_i)$. Complement coding in combination with the fast learning procedure assure that all committed weight vectors initially have the same norm value $|w| = M$ that can only decrease during updates.

B. Fuzzy ARTMAP

Fuzzy ARTMAP [9] combines two ART modules ART^a and ART^b and associates its category nodes F_2^a and F_2^b with each other by means of a *mapfield* F^{ab}. The previously fixed vigilance parameter ρ^a can temporarily increase due to a predictive mismatch of the mapfield at ART^b. Thus, the structure of ARTMAP results in a predictive module that predicts the active category J^b in F_2^b by means of the active category J^a in F_2^a and its mapfield associations.

More formally, the weight vectors w_{jk}^{ab} represent the connections between categories j in F_2^a and category k of the mapfield nodes F^{ab}. Categories k have a one-to-one correspondence with the categories in F_2^b. Thus, an active node k in F^{ab} either corresponds to a prediction of node k in F_2^b or to an actual activity of F_2^b. Similarly to fuzzy ART, a vigilance threshold ρ^{ab} is used to decide if the activation is in resonance.

$$\frac{|x^{ab}|}{|y^b|} \geq \rho^{ab} \tag{5}$$

where

$$x^{ab} = \begin{cases} y^b \wedge w_J^{ab} & \text{if the } J\text{th node in } F_2^a \text{ and } F_2^b \text{ are active} \\ w_J^{ab} & \text{if only the } J\text{th node in } F_2^a \text{ is active} \\ y^b & \text{if only } F_2^b \text{ is active} \\ 0 & \text{if neither is active} \end{cases}$$

If Equation 5 is not satisfied, parameter ρ^a is increased so that $\rho^a > \frac{|x^a|}{|I^a|}$ causing ART^a to choose another category as the currently active category or the commitment of a new category node. Parameter ρ^a is reset to a baseline value $\overline{\rho^a}$ once resonance is achieved.

Learning of the mapfield is accomplished by setting all weights initially to $w_{jk}^{ab}(0) = 1$. During resonance with the ART^a category J active, w_J^{ab} approaches the map field vector x^{ab}.

$$w_J^{ab}(new) = \beta^{ab}(w_K^b \wedge w_J^{ab}(old)) + (1 - \beta^{ab})(w_J^{ab}(old)) \tag{6}$$

With fast learning, w_J^{ab} is set directly to w_K^b which is a permanent association. Note that this fast learning approach basically maps each category J^a to one category J^b.

C. ARTMAP Becomes Bidirectional

Previous work on a somewhat bidirectional system has been undertaken in [12] introducing the *adaptive resonance associative map (ARAM)*. ARAM simplifies ARTMAP in that it gets rid of the additional mapfield nodes F^{ab}. ARAM works bidirectionally but it is only capable of handling one-to-one correspondences. We will see that our system also works bidirectionally but is is capable of learning not only one-to-one but also one-to-many and even many-to-many associations.

Bidirectional ARTMAP (BiARTMAP) is endowed with an additional mapfield with weight vectors w_{kj}^{ba} which allow the prediction of active categories F_2^a in ART^a given current activity of F_2^b in ART^b. The two mapfields x^{ab} and x^{ba}, consequently, make the system bidirectional. Resonance and learning processes are modified in that dependent on which update is processed first, the processes flow in one or the other direction. If I^b is received first, category K in ART^b is generated first staying fixed over the learning iteration. Match tracking is activated in ART^a by activating the resonance threshold ρ^{ab}. Thus, vigilance threshold ρ^a might be temporarily increased. Similar, if I^a is processed first, category J in ART^a will be fixed, threshold ρ^{ba} is activated resulting in match tracking in ART^b and a possible (temporary) threshold increase in ρ^b.

Learning is modified in that the two mapfield vectors are updated dependent on whether input I^a or I^b is processed

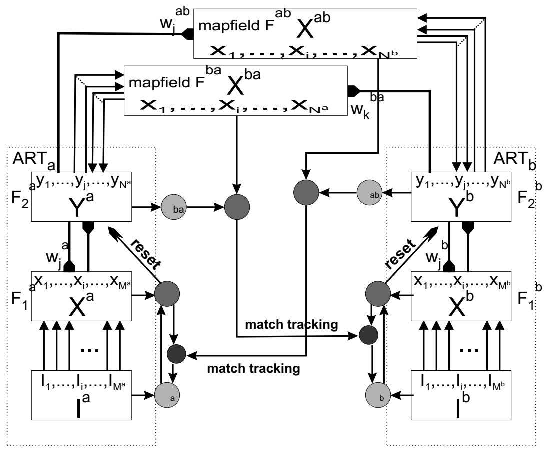


Fig. 2. Fuzzy BiARTMAP: Inputs I^a and I^b need to be in complement coding form or $|I^a|$ and $|I^b|$ need to be constant for all inputs. Match tracking can now take place in either ART system dependent on which input is processed first. Not shown is the inhibition of the other match tracking process which should take place once one mapfield is active.

first. If I^b is received first, weights w^{ab} are updated according to Equation 6 and weights w^{ba} are updated as follows:

$$w_K^{ba}(new) = \beta^{ba}(w_J^a \vee w_K^{ba}(old)) + (1-\beta^{ba})(w_K^{ba}(old)) \quad (7)$$

Hereby, operator $\vee$ denotes the fuzzy 'or' operator, that is, $a_i \vee b_i = max(a_i, b_i)$. If I^a is processed first, the updates of weights w^{ab} and w^{ba} are reversed.

$$w_K^{ba}(new) = \beta^{ba}(w_J^a \wedge w_K^{ba}(old)) + (1-\beta^{ba})(w_K^{ba}(old)) \quad (8)$$

$$w_J^{ab}(new) = \beta^{ab}(w_K^a \vee w_J^{ab}(old)) + (1-\beta^{ab})(w_J^{ab}(old)) \quad (9)$$

Thus, dependent on the input direction, weights of the one or the other input are decreased whereas the others are increased.

D. Predictions and Mirroring via BiARTMAP

We are now ready to define how BiARTMAP can be used to predict input as well as how it intrinsically functions similar to a mirror-neuron system. Figure 2 shows the BiARTMAP system schematically. The second mapfield and the potential match tracking in ART^b are unique to BiARTMAP.

Note that due to its bidirectional capabilities, either input can be predicted given the contralateral input. Let us focus on the case when input I^a to ART^a is available. Activities in ART^b can be predicted by means of the w_{jk}^{ab} weights and further according to the w_k^b weight vectors of ART^b given activity of category J in F_2^b. The active category K' in F_2^b can be predicted by

$$K' = arg \max_{k \in \{1,\ldots,N^b\}} w_{Jk}^{ab} \quad (10)$$

More challenging is the prediction of the actual input to ART^b. Since the activity of F_2^b may not be restricted to one active category, the degree of activity can be taken into account to determine the activity of the input layer $F_1^{b'}$ in expectation of input I^b,

$$F_1^{b'} = \bigwedge_{k \in \{1,\ldots,M^b\}} w_{Jk}^{ab} w_k^b \quad (11)$$

where operator $\bigwedge$ denotes the fuzzy 'and' operator applied on a set of vectors, that is,

$$\bigwedge_{i \in 1,\ldots,n} v_i = (\min_{i \in \{1,\ldots,n\}} v_{1i}, \ldots, \min_{i \in \{1,\ldots,n\}} v_{mi}) \quad (12)$$

The prediction is consequently a broad one expecting essentially all possible input patterns 'imaginable'. More formally, we are interested in the *maximal fuzzy subset* of all possible actual outcomes. Similar predictions are possible in the other directions. That is, given input I^b to ART^b we can similarly predict the expected active category in ART^a and/or the expected input to ART^a.

The reader might have deduced by now why this system might be comparable to a mirror neuron system. Essentially, using the architecture as an adaptive behavior architecture action codes may be provided to ART^b and consequent sensory changes may be provided to ART^a. Given this input configuration, the associations formed by the two mapfields will link (executed or 'imagined') actions to sensory changes as well as (perceived or 'imagined') sensory changes to possible actions that could have caused those changes. Thus, executing a particular action will result in neural activity of the specific action category making the system ready for actual sensory changes. Perceiving actual sensory changes, on the other hand, will result in a similar neural activity of the actions that *could have caused those changes*. Thus, *similar neurons are active when an action is executed but also when only the changes caused by a similar action (possibly executed by another entity) are perceived*. The next section investigates an experiment in which exactly this capability is evaluated in a simple adaptive behavior experiment.

III. BiARTMAP in a Simple Blocks World Experiment

To evaluate performance of BiARTMAP we apply the system to a simple blocks world problem. Our experiments show that BiARTMAP is able to learn an accurate representation of the environment efficiently associating possible actions with consequent changes. Moreover, we show the capability of BiARTMAP to predict action categories, effect categories, sensory changes, and action codes. Current limitations and suggestions for future work are outlined.

A. The Blocks World Problem

The blocks world problem used herein was previously investigated in [13], [14]. The world is a typical example of an environment in which *manipulative actions* can be executed. That is, actions manipulate the environment but not the perceptual field as opposed to *movement actions* which change the perceptual field but not the state of the environment (excluding the agent).

The blocks world is kept discrete and deterministic. It consists of s stacks and b blocks that can be randomly distributed over the stacks. The blocks can be manipulated by a gripper that can grip and release blocks on each stack. Each stack is coded by b attributes, denoting the presence of a block on each of the b possible positions on the stack. An

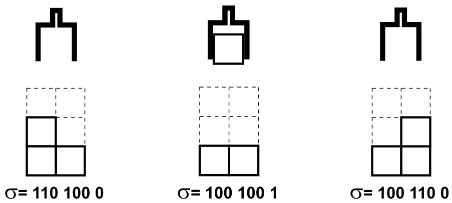


Fig. 3. Three possible successive situations in the small blocks world setting with corresponding state codes σ.

additional attribute is provided that denotes if the gripper is currently holding a block. Thus, the state space is coded by a sensory string of $sb+1$ attributes denoting a block by 1 and a free position by 0 (i.e. $X \subset \{0,1\}^{sb+1}$). Since the sensory input determines the exact actual state of the environment, the defined blocks world is a Markov decision process (MDP) (see e.g. [15] for this characteristic). Gripping and releasing actions on each stack are denoted by $U(x) = \{g1, r1, ..., gs, rs\}$ $\forall x \in X$. If there is no block to grip or the gripper is already holding a block, a gripping action has no effect. Similarly, if the gripper is not holding a block and is trying to release, the action has no effect. Figure 3 shows some blocks world states with the corresponding sensory code.

BiARTMAP senses the blocks world at discrete time steps. ART^a receives sensory changes while ART^b receives action codes. A change from 0 to 1 (i.e. a block appears) is denoted by a 1, a change from 1 to 0 with a 0 and no change with 0.5. Complement coding is applied so that the actual input string to ART^a has the length $M^a = 2(sb+1)$. In our example in Figure 3, the actual input to ART^a would be $(.5, .0, .5|.5, .5, .5|1.|.5, 1., .5|.5, .5, .5|0)$ for the change from the left-most state to the middle state. Actions are coded using one bit to specify if the action is a gripping (0) or releasing (1) action and $\lceil log_2 s \rceil$ more bits to specify the position of the action in binary.

In our applied adaptive behavior framework, actions are executed at random. Only sensory changes are fed into the network. This restriction is applied since the effect "no change" (input = $\{0.5\}^{2(sb+1)}$) can occur for all actions. Actions are presented prior to action-effects so that ART^a might increase its vigilance threshold ρ^a to accomplish resonance in the mapfield.

B. Performance

We first apply BiARTMAP to a very small setting with two stacks and three blocks, only. Parameters are set to $\overline{\rho^a} = 0$, $\overline{\rho^b} = 1.0$, $\beta = 1$, and $\alpha = 0.001$. Note that we set the learning rate β to one which is rather harsh. In future work, it is necessary to experiment with other values of β. Also, the *moyenne adaptive modifiée* technique [16] seems to be applicable in this respect in which β effectively decreases to a fixed value resulting in strong adaptation early on and a slow adaptive process later in the run.

The resulting weight matrices and mapfield matrices are shown in Table I. The mapfield vectors w_j^{ab} ($ART^a \rightarrow ART^b$) and w_k^{ba} ($ART^b \rightarrow ART^a$) show how BiARTMAP links

TABLE I

RESULTING WEIGHT VECTORS IN THE BLOCKS WORLD WITH $s = 2$ STACKS AND $b = 3$ BLOCKS.

$ARTa : w_j^a$ vectors

.5	.5	.5	.0	.0	.0	1.	.5	.5	.5	.5	.5	.5	.0
.5	.5	.5	.5	.5	.5	.0	.5	.5	.5	.0	.0	.0	1.
.5	.5	.5	.5	.5	.5	.0	.5	.0	.0	.5	.5	.5	1.
.5	.0	.0	.5	.5	.5	1.	.5	.5	.5	.5	.5	.5	.0
.0	.5	.5	.5	.5	.5	1.	1.	.5	.5	.5	.5	.5	.0
1.	.5	.5	.5	.5	.5	.0	.0	.5	.5	.5	.5	.5	1.

$ARTb : w_k^b$ vectors

.0	1.	.0	1.	.0	1.
1.	1.	.0	.0	.0	1.
1.	.0	.0	.0	1.	1.
.0	.0	.0	1.	1.	1.

w_j^{ab} vectors

1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1
0	0	0	1
0	0	1	0

w_k^{ba} vectors

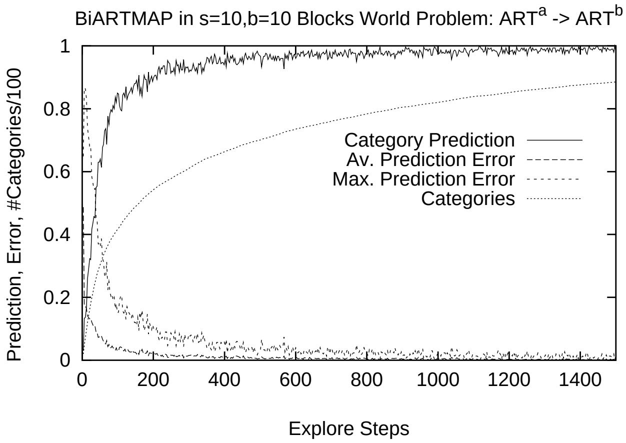
1	0	0	0	0	0
0	1	0	0	0	0
0	0	1	0	0	1
0	0	0	1	1	0

action-effects (processed in ART^a) to the corresponding actions (processed in ART^b) and vice versa. Taking a closer look at the mapfield weights w_j^{ab} that link action-effects (ART^a categories) to the corresponding actions (ART^b categories), we can see that w_4^a as well as w_5^a are linked to action category four (which is specified to be a grip on first position—action code 000111). Vector w_4^a covers the cases in which the second or third block is gripped from the first stack whereas w_5^a covers the case in which the first block is gripped. Weights w_k^{ba} cover those two cases predicting the actual optimal representation (i.e. the maximal fuzzy subset of all possible outcomes) $(.0, .0, .0|.5, .5, .5|1.|.5, .5, .5|.5, .5, .5|.0)$ of all possible action-effects of action $g1$ using equation 11. Categories are correctly predicted in both directions as well. Thus, BiARTMAP generated a NN with complete and accurate mirroring capabilities: Observed changes can be instantly associated with corresponding actions—just like a real mirror-neuron system is assumed to operate.

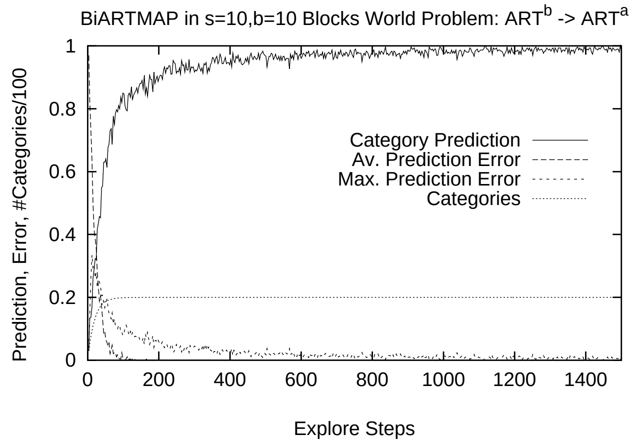
Figure 4 shows the performance of BiARTMAP in a larger setting with 10 blocks and 10 stacks. Performance is averaged over 100 experiments. The action prediction capability, given action-effects, is shown in Figure 4(a) while action-effect prediction, given actions, is shown in Figure 4(b). It can be seen that BiARTMAP learns the relations very fast. Perfect performance, however, is not reached due to the occurrence of highly improbable events (the presence of a lot of blocks on one stack which is unlikely when executing actions at random). We measure performance by determining the number of correct category predictions of the last 3 category predictions as well as determining the average prediction error over the last 3 sensory predictions and the maximal error in one attribute over the last 3 sensory predictions. An error is a prediction whose value is larger than the actual value, effectively testing if a fuzzy subset of the actual outcome was predicted. The number of categories for ART^a become rather large which suggests the need for a generalization mechanism in the system. The number of categories in ART^b equals the 20 possible actions. The results confirm the bidirectional predictive capabilities and thus, the mirror property of the resulting system.

IV. RELATION TO RESEARCH IN PSYCHOLOGY

Additional to its relation to mirror neurons, BiARTMAP appears to be related with several other research directions in psychology including the importance of anticipatory learning



(a) Action prediction



(b) Effect prediction

Fig. 4. Performance of BiARTMAP shows that it is capable of evolving a mirror representation in the blocks world problem. BiARTMAP is soon capable of predicting the corresponding action code, or action-effect, reliably

and behavior, attentional processes, and the representation of sensory-motor contingencies.

The movement away from the pure stimulus-driven behavior taught during *behaviorism*, dates back to Tolman's discovery of *latent learning* (learning of environmental structure and behavioral exploitation of this knowledge) [17]. Recent psychological literature increasingly explores learning and exploitation of action-effect relations instead of stimulus-response relations. Hoffmann outlined a learning theory called *anticipatory behavioral control* [18], [19] that accounts for the observations of latent learning, effect influences on action execution, as well as other stimulus and effect impacts on learning and behavior. Similar to the anticipatory behavioral control theory, BiARTMAP primarily establishes action-effect connections.

Additionally, attentional processes can be implemented predisposing BiARTMAP to expectable action-effects. Top-down action-driven attentional processes originated in ART^b can make the system ready to process expectable sensorial changes (*preparatory attention*).

Another interesting relation of BiARTMAP can be found due to its capability of learning and representing the recently proposed sensory-motor contingencies. O'Regan and Noë argue that the experience of 'feel' and ultimately "visual consciousness" may emerge out of the "mastery" of currently imaginable sensory-motor contingencies [20]. Although BiARTMAP currently does not consider environmental context, sensory-motor contingencies are directly represented. Grossberg even argues that all conscious states in the brain are resonant states [21]. BiARTMAP couples several ART systems and thus couples several resonant states. Although comparisons to such high level cognitive functions are certainly far fetched, the similarities remain astonishing.

Coming back to the mirror neuron comparison it needs to be criticized that perceptual changes might differ dependent on if the action was executed or observed. However, it is currently not known how the projection of the other individual's perspective may work. Assuming such a process, our approach is intended to show how a mirror system could function.

Another critical point is that currently BiARTMAP relates any perceived changes to its own actions. In general, the activity of mirror neurons seems to be correlated with intentional, or *goal-directed*, behavior [2]. BiARTMAP cannot distinguish sources of change or even intentions. Such distinctions can only be accounted for if *situational dependencies* are incorporated and BiARTMAP is combined with a *behavioral module*. Despite these challenges, the many similarities suggest that BiARTMAP forms a proper basis for a simulation of mirror neurons.

V. Possible Enhancements

The last sections showed that currently BiARTMAP lacks the incorporation of situational dependencies as well as behavioral capabilities.

To distinguish different situational dependent action-effect relations with BiARTMAP, we suggest the addition of another fuzzy ART system ART^c that processes sensory input. ART^c may be linked to ART^a by a mapfield that combines categories of ART^b and ART^c and similarly, it may be linked to ART^b by a mapfield that combines categories of ART^a and ART^c as sketched in Figure 5. Match tracking might be triggered in ART^c parallel to ART^b (ART^a) or it may be passed on once match tracking fails in ART^b (ART^a). Consequently, the system would be destined to seek an explanation for any observed action-effect.

The integration of BiARTMAP with a behavioral module points to an interesting relation of the sensory changes coded in ART^a and the difference vector (DV) in the *vector associative maps* VAM [22]. Given the VAM architecture, a difference

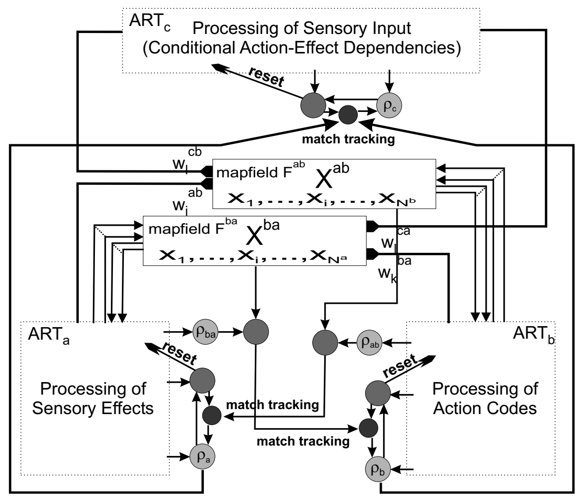


Fig. 5. Proposed architecture of BiARTMAP with additional conditional dependencies.

vector is generated by representing the difference between the present position command (PPC) and the target position command (TPC). This difference effectively corresponds to the differences processed in ART^a which can then, due to the learned associations to motor commands, cause action execution and action control. Interestingly, this proposition strongly corresponds to the theory of anticipatory behavioral control outlined above.

VI. Summary and Conclusions

This paper introduced the bidirectional ARTMAP system *BiARTMAP*. ARTMAP was usually restricted to applications in supervised classification problems providing problem instances to the ART^a module and the corresponding classes to the ART^b module. BiARTMAP departs from this unidirectional characteristic of ARTMAP making it *bidirectional*. As an adaptive behavior system, BiARTMAP is a *self-supervised* learning system associating executed actions with the resulting sensory consequences. The diverse relations to cognitive psychology and neuroscience promise fruitful future investigations and applications of BiARTMAP. The most striking similarity can be found in the comparison to mirror neurons. Similar to mirror neurons, same neurons are active when executing an action but also when observing similar sensory changes (action-effects).

While BiARTMAP is currently only capable of relating action-effects with action codes, it was outlined how sensory dependencies might be included as well as how the module might be integrated into a (goal directed) behavioral module. Despite the appealing relation to mirror neurons in the presented experiment, we want to point out that BiARTMAP is certainly not restricted to such input patterns. In fact, any classification or associative patterns should be learnable. Future research needs to investigate those promising capabilities of BiARTMAP.

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