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ABSTRACT
This article presents a new neural pattern recognition architecture on multichannel data representation. The architecture employs generalized ART modules as building blocks to construct a supervised learning system generating recognition codes on channels dynamically selected in context using serial and parallel match tracking led by inter-ART vigilance signals.

1 Introduction
ARTMAP is a neural network architecture for supervised learning of recognition categories (Carpenter, Grossberg, & Reynolds, 1991; Carpenter, Grossberg, Markuzon, Reynolds, & Rosen, 1991a). It consists of a pair of ART networks, ART 1 or Fuzzy ART (Carpenter & Grossberg, 1987a; Carpenter, Grossberg, & Rosen, 1991b), linked together via an inter-ART associative memory, called a map field. The superiority of the architecture to other commonly used neural networks in terms of speed of learning was demonstrated elsewhere (Carpenter, Grossberg, & Iizuka, 1992).

In many pattern recognition tasks, input patterns have multichannel representations, where each channel provides a feature vector of different nature or different level. Multiresolution, or pyramid, image representation used in machine vision is an example of multichannel data representation; another example can be found in tasks of multiple sensory inputs fusion.

In this article, I propose a new neural network architecture which is a generalization of ARTMAP for a pattern recognition system which takes input from a multichannel path. This generalization is accomplished by replacing the pair of ART networks in ARTMAP with a pair of generalized ART modules which can account for multichannel data processing, where the generalized ART module is a neural network belongs to a class defined as a functional generalization of ART networks such as ART 1, ART 2 (Carpenter & Grossberg, 1987b), or Fuzzy ART. The term ART-module will be used instead of the term "generalized ART module," hereafter.

In this article, three classes of ART-module are introduced: an elementary module with a single channel, a parallel processing module employing a parallel match tracking on multiple channels, and a serial processing module employing a serial match tracking on multiple channels.

2 ART-modules as building blocks
The ART-module is defined functionally as a self-organizing unsupervised learning system whose interface consists of two arrays of terminals, one for receiving an input pattern and the other one for sending an output pattern, as well as four control terminals: Vin receiving an inter-ART vigilance signal, Vout sending an inter-ART vigilance signal, R sending a resonance signal, and A accepting an arousal signal (Figure 1.a). I use symbols Vin, Vout, R, A, etc. to represent the labels of the terminals as well as the activity levels of these terminals.

These control terminals can take only binary activity levels, 1 (ON) and 0 (OFF) and satisfy following conditions: (1) (A) If A = 1 and |I| > 0, then the module is active, where I represents the input vector to the module. (2) (R) If R = 1, the module is in a resonant (stable) state. (3) (Vin) Activation of Vin while R = 1 causes increase of sensitivity level of the module to mismatch, where the sensitivity level is a generalization of the vigilance parameter $\rho$ of ART network, and in absence of Vin activity, the sensitivity level relaxes to its baseline state. Sustained activity

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of $Vin$ causes successive resets of the output pattern, each time to a better matching code, until the sensitivity level reaches an upper limit ($\leq 1$). If the sensitivity level reaches the upper limit, activation of $Vout$ follows. This modulation of sensitivity is assumed to occur at a rate slower than node activation and faster than learning so that after each reset there is a period of time, before next reset will occur, which is long enough for the modulation of cell activities to be stabilized. On the other hand, activation of $Vin$ while $|I| = 0$ makes $Vout$ active. Finally activation of $Vin$ while $|I| > 0$ and $A = 0$ triggers sustained activity on the terminal $A$. This activity remains until the input $I$ is shut off. (4) ($Vout$) The terminal $Vout$ can be active only if $Vin = 1$. Conversely, $Vout = 1$ means the sensitivity level of the module has reached its upper limit.

Then a group of ART-modules, each processing a particular channel, are synthesized by a higher order ART-module to construct a parallel processing module or a serial processing module as described in the next two sections. An important property of these constructions is that the constructed modules again satisfy the definition of ART-module. This self similarity makes the
nested use of the modules to construct a conglomerate of ART-modules possible.

In the same way as a pair of ART 1 or Fuzzy ART networks are used in ARTMAP to realize supervised learning, any pair of ART-modules can be embedded in an ARTMAP architecture (Figure 1.b), where an inter-ART vigilance signal evoked by a mismatch in the map field of the ARTMAP may trigger an avalanche of inter-ART vigilance signals in the ART-module.

The simplest realization of ART-module, called elementary module, consists of an ART network, such as ART 1, ART 2, ART 3 or Fuzzy ART, and some auxiliary mechanisms which endow the module with the properties required for ART-module. Figure 2 depicts an example of elementary module constructed on the basis of an ART 1 network.

3 Parallel processing module

The parallel processing module is designed to process multichannel data, where the channels have the same level of information granularity, or importance, a priori. Although similar architectures were proposed recently (Zalama, Díaz-Pernas, Dimitriadis, & Coronado, 1993), the parallel match tracking mechanism essential in the present architecture was not employed in their architectures.

A parallel processing module, labeled P, with n input channels consists of n lower ART-modules, labeled ARTi, 1 ≤ i ≤ n, and an upper ART-module, labeled ART2. The modules ARTi are responsible each to a particular channel and ART2 combines the outputs of ARTi into a higher level category code (Figure 3). The dynamics of the module is controlled by two component systems: an arousal system controlling the timing of processings so that the module ART2 waits to start processing until all ARTi reach their resonant states and an inter-ART vigilance system controlling the parallel match tracking among the modules ARTi.

While the terminal Vin receives ON signal, the signal is transmitted to the terminal Vin2 and a match tracking in ART2 ensues until it finds a better matching code which satisfies the map field matching criterion of ARTMAP while keeping input from lower ART-modules ARTi una.ltered or it gives up to find such a code. In the later case, the terminal Vout2 sends an inter-ART vigilance signal to all Vini followed by simultaneous match trackings in all ARTi. This parallel match tracking may cause a number of resets in ARTi which, in turn, may trigger resets in ART2. It is easily verified that a parallel processing module satisfies the formal definition of ART-module.

4 Serial processing module
Figure 4: Structure of a serial processing module is depicted in the upper rectangle where the lateral inter-module connections are omitted. The lower part surrounded by an oval shows a part of omitted lateral connections which lie between ART$_{1i}$ and ART$_{1(i+1)}$. The dotted (resp. thin solid) lines are the signal pathways included in the inter-ART vigilance (resp. arousal) system.

The serial processing module is designed to process multiple channels which have serially ordered levels of information granularity or importance. The strategy of coarse-to-fine matching is a typical example requiring this type of processing. In the present architecture, dynamical selection of appropriate levels in response to each input pattern diminishes the code complexity.

Similarly to the parallel processing module, a serial processing module, labeled $S$, consists of $n$ lower ART-modules, labeled ART$_{1i}$, $1 \leq i \leq n$, and an upper ART-module, labeled ART$_2$, as well as an arousal system and an inter-ART vigilance system (Figure 4).

In the parallel processing module, there are but afferent and efferent connections between lower and upper modules; in contrast, there exist lateral adaptive connections which orient attention to the module of adequate level. These adaptive connections are included in the arousal system. An adaptive connection from each output terminal $O_j$ of ART$_{1i}$ to the terminal $A_{1(i+1)}$ of ART$_{1(i+1)}$ module has an adaptive weight $W_j$ which samples $A_{1(i+1)}$ activity when $O_j$ is active.

The dynamics of a serial processing module is analyzed as follows: (1) ($A = 1$) If $A$ is activated, this activation is first transmitted to $A_{11}$ of ART$_{11}$. Then when ART$_{11}$ reaches resonant state, its resonance signal excites cell $C_1$ and if the weight $W_j$ of the connection from the active output node $O_j$ to the terminal $A_{12}$ is not large enough to activate the terminal $A_{12}$, cell $C_1$ sends an arousal signal to the module ART$_2$. Otherwise the terminal $A_{12}$ becomes active and this activity inhibits cell $C_1$. Hence the module ART$_2$ remains inactive and the module ART$_{12}$ is activated. The same process will be repeated until the condition $R_{1i} = 1$ and $A_{1(i+1)} = 0$ holds. When this
condition holds, the module \( ART_2 \) becomes active. (2) \( (A = 1 \text{ then } V_{in} = 1) \) When the terminal \( V_{in} \) receives ON signal, the signal is transmitted to \( V_{in2} \) and a match tracking in \( ART_2 \) ensues exactly same as in the case of parallel processing module. When the module \( ART_2 \) gives up the match tracking, \( ART_2 \) sends an inter-ART vigilance signal to the module \( ART_{11} \) which triggers an avalanche of inter-ART vigilance signals; \( ART_{11} \rightarrow ART_{12}, ART_{12} \rightarrow ART_{13}, \) and so on. This avalanche continues until \( V_{in} \) is shut off. Once \( V_{in(i+1)} \) triggers sustained activity on \( A_1(i+1) \), this activity won’t vanish until the input \( I \) is shut off. Hence if \( J \)-th output terminal of \( ART_{11} \) is active, the adaptive weight \( W_j \) learns \( A_1(i+1) \) activity to approach 1. (3) \( (V_{in} = 1 \text{ while } A = 0) \) If \( V_{in} \) becomes active while \( A \) is inactive, the active potential is transmitted to \( V_{in11} \) via the pathway \( V_{in} \rightarrow V_{in2} \rightarrow V_{out2} \rightarrow V_{in11} \), since “\( A = 0 \)” means \( ART_2 \) receiving no input. Then the activation of \( V_{in11} \) triggers sustained activity on \( A_11 \). Consequently, the terminal \( A \) becomes active and the processes in (1) and (2) follow in this order.

The complete analysis of the dynamics when ART-modules are embedded in ARTMAP architecture can be carried out as in the cases of the original ARTMAP and Fuzzy ARTMAP.

5 Conclusion
In this article, I have proposed a new architecture for pattern recognition system on multichannel input representation, where recognition codes are generated using parallel and serial match trackings led by inter-ART vigilance signals among ART-modules to realize context dependent adaptive codings. The building block concept endows the architecture with design flexibility and productivity. As such, it offers a useful tool for many pattern recognition tasks where input patterns are represented as combinations of features of different natures.

In contrast, the contribution may be extended to elucidate the biological visual recognition strategy based on the existence of multiple channels both in terms of feature and spatial scale.

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Reference


