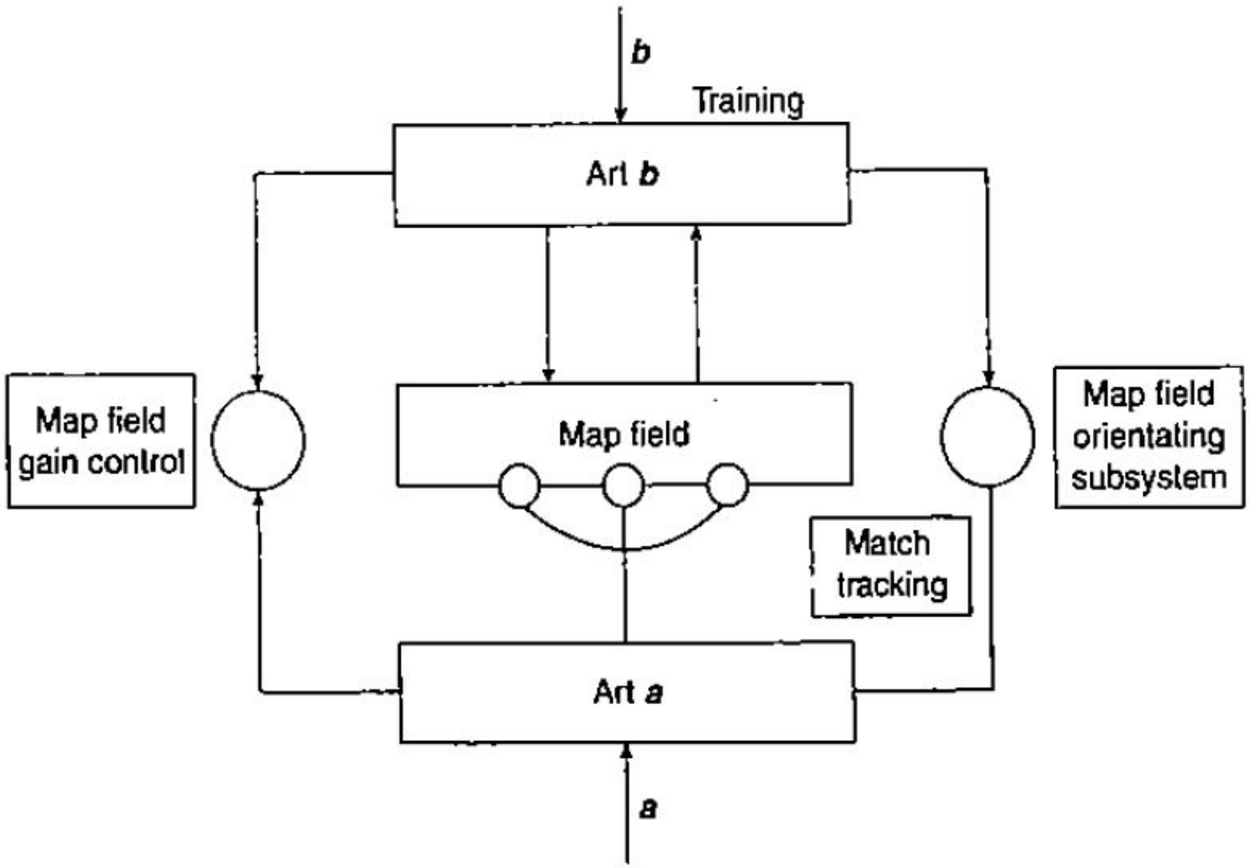
Simplified fuzzy ART systems

ART is a neural network topology whose dynamics are based on Adaptive Resonance Theory (ART). ART networks follow both supervised and unsupervised algorithms.

ARTMAP : Also known as predictive ART. It combines two slightly modified ART-1 or ART-2 units into supervised learning structure. Here, the first unit takes the input data and the second unit takes the correct output data, then used to make the minimum possible adjustment of the vigilance parameter in the first unit in order to make the correct classification.

- **Fuzzy ARTMAP** is neural network architecture for conducting supervised learning in a multidimensional setting. When Fuzzy ARTMAP is used on a learning problem, it is trained till it correctly classifies all training data. This feature causes Fuzzy ARTMAP to ‘over-fit’ some data sets, especially those in which the underlying pattern has to overlap. To avoid the problem of ‘over-fitting’ we must allow for error in the training process.



b
Training
Art b
Map field gain control
Map field
Map field orientating subsystem
Match tracking
Art a
a

Here, two ART modules are linked by an inter-ART module called the Map Field. The Map Field forms predictive associations between categories of the ART modules and realizes a match tracking rule. If ARTa and ARTb are disconnected then each module would be of self-organize category, groupings their respective input sets.

- In supervised mode, the mappings are learned between input vectors ***a*** and ***b***

Soft computing based Fuzzy Logic Controllers.

- Traditional methods, which address robotics control issues, rely upon strong mathematical modeling and analysis.
- For unstructured environment – traditional methods is not suitable.
- Under such circumstances fuzzy logic can be effectively used.
- Fuzzy controllers and their hybridization with other systems are ease to design and implement.

- Three major control issues are
- (i) control of direct drive robot motors
- (ii)control of flexible links
- (iii)Intelligent navigation of mobile robots.

- Three methods are employed
- Neuro fuzzy
- GA-fuzzy
- GP-fuzzy

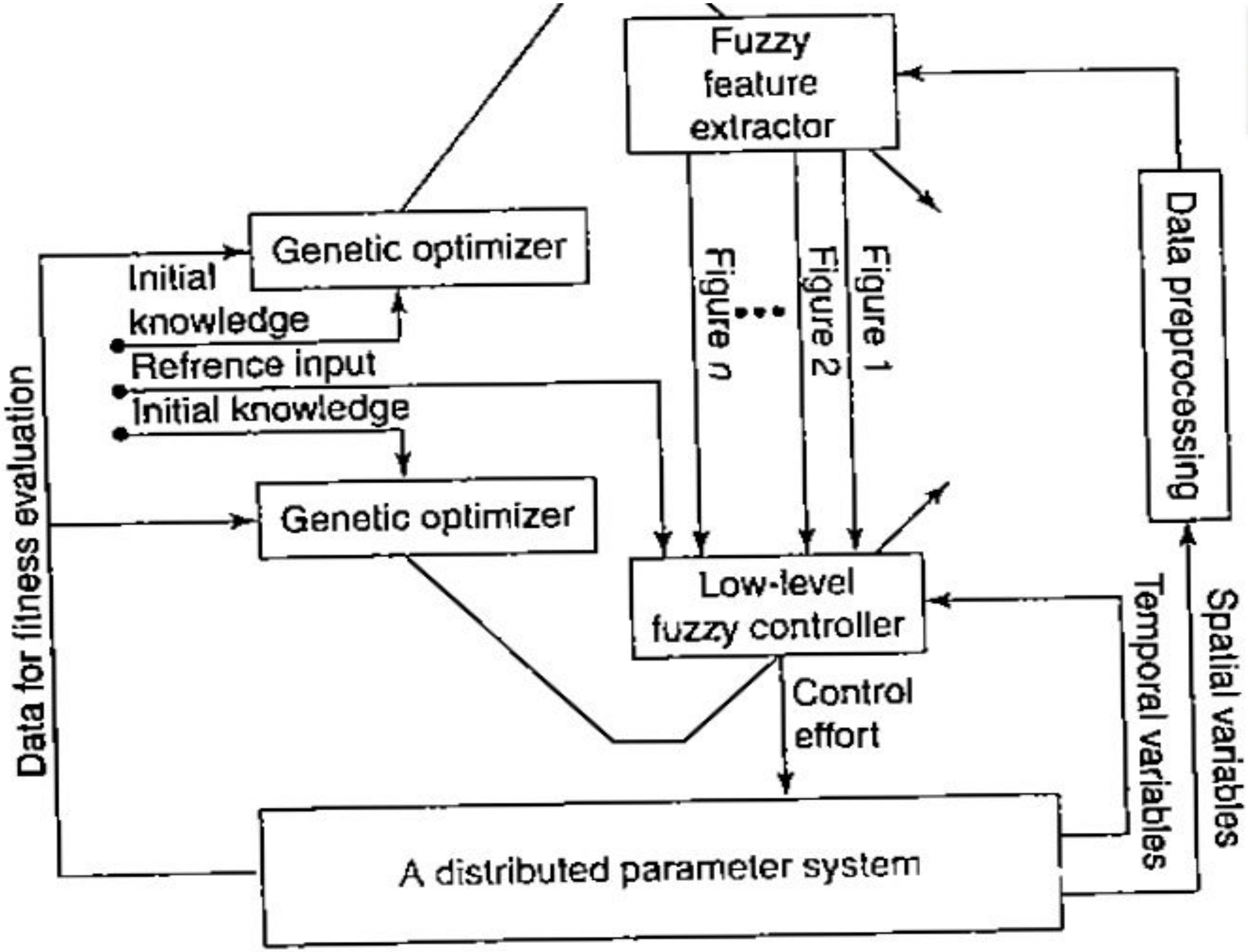
- Three soft computing hybrid fuzzy paradigms for automated learning in robotic systems are used.
- The first scheme concentrates on a methodology that uses neural networks (NNs) to adapt a fuzzy logic controller (FLC) in manipulator control tasks.
- The second paradigm develops a two-level hierarchical fuzzy control Structure for flexible manipulators. It incorporates GAS in a learning scheme to adapt to various environmental conditions.
- The third paradigm employs GP to evolve rules for fuzzy behaviors to be used in mobile robot control.

Neuro fuzzy

- A multilayer perceptron NN is used to classify the temporal response of the system into different patterns. Depending on the type of pattern such as" response with overshoot," "damped response," "oscillating response," etc. The scaling factor of the input and output membership functions is adjusted to make the system respond in a desired manner.

- The FLC algorithm requires processing of several functionalities such as fuzzification, inferencing and defuzzification. This can be achieved by a multiprocessing architecture.

GA Fuzzy



Fuzzy feature extractor
Genetic optimizer
Initial knowledge
Refrence input
Initial knowledge
Genetic optimizer
Figure n
Figure 2
Figure 1
Data preprocessing
Low-level fuzzy controller
Control effort
Temporal variables
Spatial variables
Data for fitness evaluation
A distributed parameter system

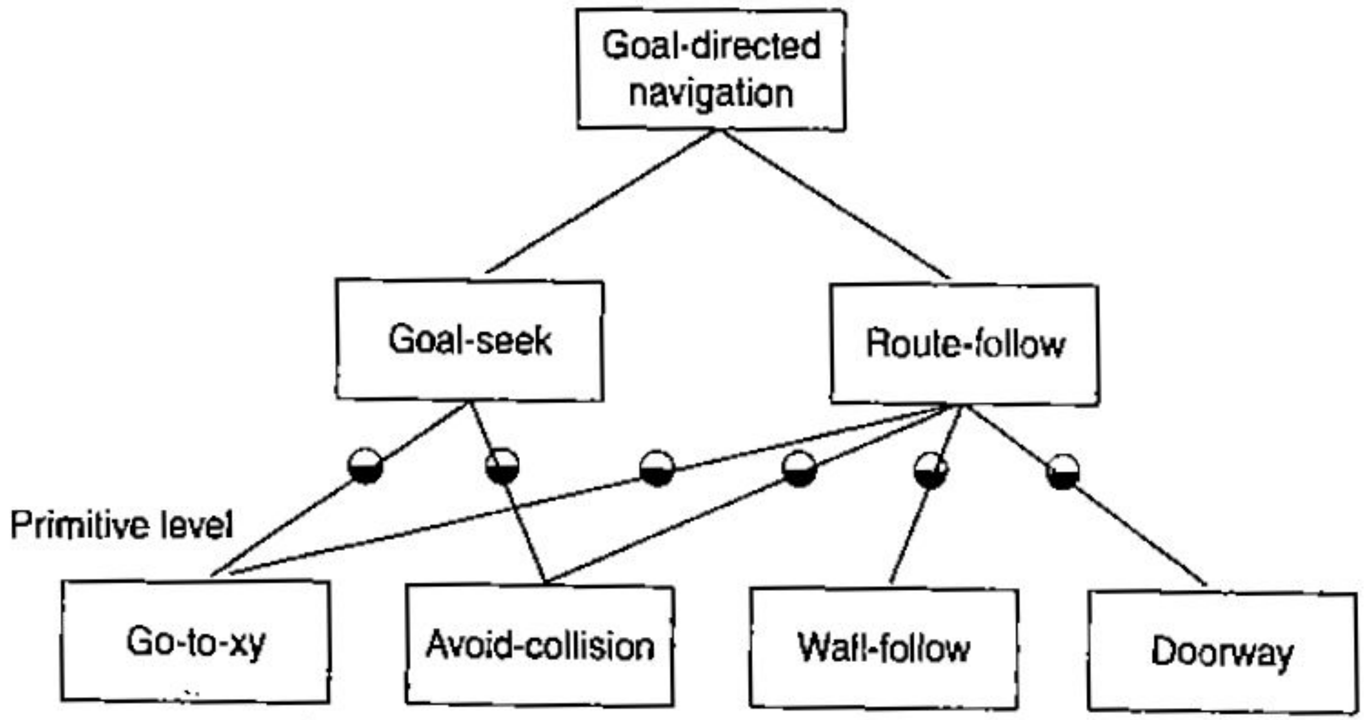
- Within the hierarchical control architecture, the higher level module serves as a fuzzy classifier by determining spatial features of the arm such as *straight, oscillatory, curved. This information is supplied to the lower level of hierarchy where it is processed among other sensory* information such as errors in position and velocity for the purpose of determining a desirable control input(torque).
- The following fitness function *was used to evaluate individuals within a population of potential solutions:*

$$\text{Fitness} = \int_{t_s}^{t_f} \frac{1}{e^2+\gamma^2+1}\,dt$$

where e represents the error in angular position and γ represents overshoot. Consequently, a fitter individual is an individual with a lower overshoot and a lower overall error (shorter rise time) in its time response. Here, results from previous simulations of the architecture are applied experimentally. The method of *grtd-parenting* was used to create the initial population.

GP Fuzzy

- For mobile robot behavior .GP based hybrid FLC is used. All rule bases in the initial population are randomly created, but descendant populations are created primarily by reproduction and crossover operations on rule base tree structures.
- For the reproduction operation several rule bases selected on the basis of superior fitness are copied from the current population into the next, i.e., the new generation. The crossover operation starts with two parental rule bases and produces two off springs that are added to the new generation. The operation begins by independently selecting one random node from each parents.



Goal-directed navigation
Goal-seek
Route-follow
Primitive level
Go-to-xy
Avoid-collision
Wall-follow
Doorway

- The sub trees subtending from crossover nodes are then swapped between the parents to produce the two off springs. GP cycles through the current population perform fitness evaluation and apply genetic operators to create a new population. The cycle repeats on a generation~by~generarion basis until satisfaction of termination criteria (e.g. lack ofimprovement,
- maximum generation reached, etc.). The GP result is the best fit rule base that appeared in any generation.