Modular Connectionist Systems: Toward Higher Level Intelligent Functions

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Abstract: *Recent advances in "neurobiology" allowed highlighting some of key mechanisms of animal intelligence. Among them one can emphasizes brain's "modular" structure and its "self-organizing" capabilities. The main goal of this paper is to show how these primary supplies could be exploited and combined in the frame of "soft-computing" issued techniques in order to design intelligent artificial systems emerging higher level intelligent behavior than conventional Artificial Neural Networks (ANN) based structures..*

Keywords: Modularity, Self-Organization, Artificial Intelligent systems, Real-World applications, Implementation.

1. INTRODUCTION

Much is still unknown about how the brain trains and self-organizes itself to process so complex information. However, the recent advances in "neurobiology" allowed highlighting some of key mechanisms of animal (and human) intelligence. In fact, our simple and inappropriate binary technology remains too primitive to reproduce the biological complexity of these marvels mechanisms, but a number of those highlighted points could already be sources of inspiration for higher level intelligent artificial systems. Among interesting features of animal's and human's brain, one can emphasize its "modular" structure and it's "self-organizing" capabilities. If it is still early to state on "concurrent" or "cooperative" nature of ways that these complex features interact, they could already be considered as basic features in emergence of higher level artificial intelligent behavior.

On the other hand, overcoming limitations of conventional approaches thank to their learning and generalization capabilities, Artificial Neural Networks (ANN) made appear a number of expectations to design "intelligent" information processing systems. If learning and generalization capabilities of these bio-inspired connectionist models appear as central requirements in intelligent systems' design, nowadays, it is well admitted that intelligent behavior requires more sophisticated mechanisms than those performed by these "simple" models.

The main goal of this paper is to show how these primary supplies could be exploited and combined in the frame of "soft-computing" issued techniques in order to design intelligent artificial systems emerging higher level intelligent behavior than conventional Artificial Neural Networks (ANN) based structures. These foremost features have inspired a set of implementations dealing with real-world applications and covering several different areas as: robotics, image processing and pattern recognition, classification and dynamic nonlinear behavior modeling (identification and prediction).

The present paper is organized in following way: the next section will briefly introduce the general frame of modular modeling. Section 3 will describe a first applicative implementation dealing with "biometric face recognition" dilemma in the challenging frame of "mass biometry". In section 4, a different self-organizing tree-like modular system, taking advantage from a "complexity estimation" loop, will be described. Section 5 will present a modular Fuzzy-CMAC architecture dealing with fully autonomous biped robot's walking dilemma. Section 6 will give an additional applicative example of modular connectionist system dealing with nonlinear dynamic systems' behaviour identification. Finally, the last section will conclude the present article and discuss a number of perspectives.

2. GENERAL FRAME OF MODULAR MODELING

Recently, a number of works dealing with multi-modeling concept have been proposed for nonlinear systems modeling ([1] to [7]) in order to avoid difficulties (modeling complexity). In fact, taking advantage from "modularity", multi-modeling concept reduces considerably modeling or processing complexity by dividing the initial complex problem (or task) into a set of local models (or local processing modules). Adding self-organizing skill to a multi-model (or to a modular processing architecture) could lead to powerful structure, especially if local models (or local modules) are ANN based units.

From a general point of view; a multi-model is composed of several models each of which is valid in a well defined interval which corresponds to a part of the operation range of the system or covers a part of the whole feature space of the problem to be solved. The local validity of a model in a well defined interval is specified by using functions with limited supports which tend to significantly increase the contribution of the local models in that zone and tend to decrease it elsewhere. The combination of all local models allows description of the whole system's behavior. The local models participations in the multi-model's output are determined by "activation degree" associated to each local model. The action of "activation degrees" on multi-model's response could be seen as some kind of local models responses weighting fashioning its response in order to approximate the modeled behavior.

Consider a system described by the general equation

(or transfer function), expressed by relation (1), where $F(\cdot)$ represents a global unknown model (complex task to be performed, complex system to be identified, complex behavior to be described, etc…) and $\varphi(t)$ is a feature vector (characteristic vector composed by a number of features related to data to be processed, regression vector composed by a number of delayed system's inputs and outputs, etc…). The associated multi-model, composed by *M* local models (or processing units) is defined by relation (1) where $f_i(\varphi(t))$ represents the i-th local model (or local processing unit) and β_i is a parameter vector. S (.) represents a fusion operator or a selection function.

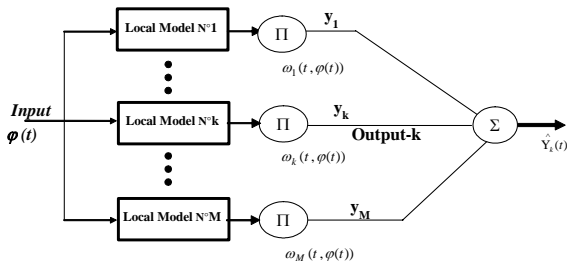$$\hat{y}(t) = S(\varphi(t), \beta) \qquad (1)$$

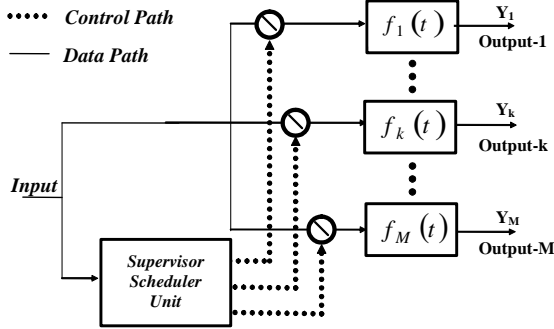**Fig.1 - General bloc diagram of a multi-model concept in the frame of the relation (2).**

Fig.2 - General bloc diagram of a multi-model concept in the frame of the relation (3).

One of the most popular fusion operators is the weighted sum function. In this case, the associated multi-model, composed by *M* local models (or processing units) and their weights $\rho_i(\varphi(t), \beta_i)$, with $\rho_i(\varphi(t)\beta_i) \geq 0$ (for all *i*) and $\sum_{j=1}^{M} \rho_i(\varphi(t), \beta_i) > 0$ (for all $\varphi(t)$), is defined by the weighted average expressed in the relation (2). In this relation $f_i(\varphi(t))$ represents the i-th local model and β_i is a parameter related to the validity function ρ_i.

$$\hat{y}(t) = \frac{\sum_{j=1}^{M} \rho_j(\varphi(t), \beta_j) f_j(\varphi(t))}{\sum_{j=1}^{M} \rho_j(\varphi(t), \beta_j)} \qquad (2)$$

Among popular selection functions is the relation expressed by (3), which depends on $\varphi(t)$, and some parameters p and/or conditions ξ. p_k represents some particular values of parameter p and ξ_k denotes some particular value of condition ξ, respectively.

$$S(\varphi(t), p, \xi) = (s_1 \quad \cdots \quad s_k \quad \cdots \quad s_M)^T$$
$$\text{with}$$
$$\begin{bmatrix} s_k = 1 & \text{if } p = p_k \text{ and } \xi = \xi_k \\ s_k = 0 & \text{else} \end{bmatrix} \qquad (3)$$

Figure 1 shows the bloc diagram of a multi-model described by relation (2) and figure 2 gives the bloc diagram corresponding to a modular structure described by relation (3).

3. MODULAR FACIAL RECOGNITION SYSTEM USING KERNEL FUNCTIONS ANN AS LOCAL PROCESSING UNITS

Contrary to "individual biometry" where both authentication and identification operations assume a precise biometrical characterization of concerned individuals, the main goal in "mass biometry" is to authenticate or identify an unusual (suspect) behavior within a flow of mass customary behaviors. That's why, in "mass biometry" the chief requirements concern on the one hand, the ability of handling patterns containing relatively poor information and on the other hand, the skill of high speed processing in order to treat a mass number of patterns in a reasonably acceptable delay (real-time). The solution we propose [8] includes three main stages. The two firsts are a video (image flow) acquisition device, which could be a standard digital video camera and an image processing stage performing a set of image pre-processing operations and extracting a number of facial biometric features. The last stage is a modular stage composed by a set of kernel functions based ANN ([9] to [12]) units carrying out classification and decision operations.
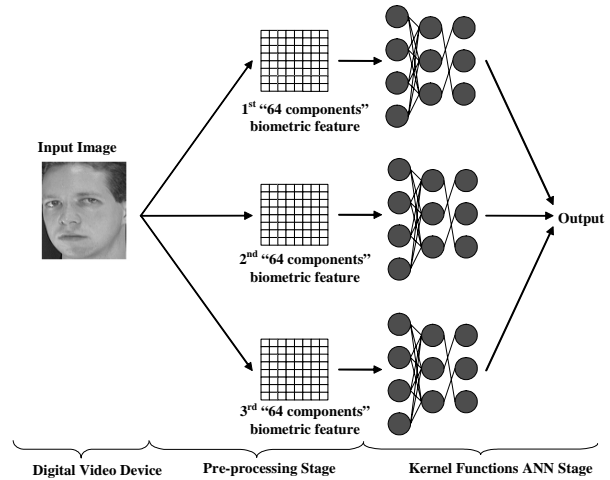

Fig.3 – Bloc diagram of the implemented modular face recognition system.

A prototype of such modular facial recognition system has been realized using three ANNs (figures 3 and 5).

Each ANN is specialized in processing of a specific kind of biometric feature extracted from the input image. Then a decision logic based procedure performs (on the basis of classification results relative to each biometric feature) the identification of the concerned individual. The implementation has been done on the basis of ZISC-036 neuro-processor based board composed by 16 chips, each one including 36 neurons ([13] to [16]).
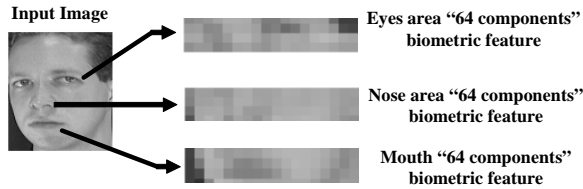
Fig.4 - Example of "localized biometric features" processed by each module composing the classification-decision stage.
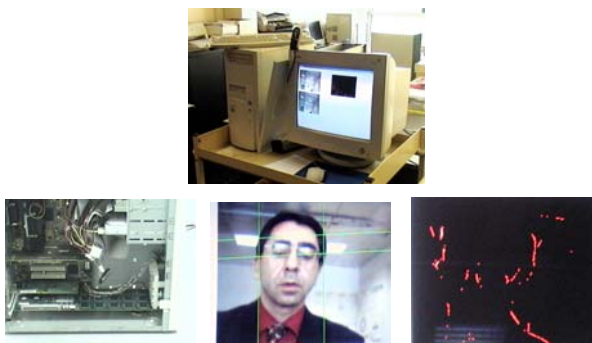
Fig.5 – Photographs, showing the implemented system (upper picture), the ZISC-036 neuro-processor based board (lower-left), and the screen of the implemented modular face recognition system (lower-middle and lower-right pictures).

The proposed solution takes advantage at the same time from kernel functions based ANN's image processing ability implemented by ZISC-036 and from the massively parallel architecture of this neuro-processor allowing very high processing speed. The obtained promising results show feasibility and effectiveness of the proposed solution reaching 85% correct identification involving a relatively weak number of learned samples (5 samples per face).

4. TREE-LIKE MULTIPLE NEURAL NETWORK MODELS GENERATOR WITH A COMPLEXITY ESTIMATION BASED DECOMPOSER

In a very large number of cases dealing with real world dilemmas and applications (system identification, industrial processes, manufacturing regulation, optimization, decision, pattern recognition, systems, plants safety, etc), information is available as data stored in files (databases etc.). So, the efficient data processing becomes a chief condition to solve problems related to above-mentioned areas. In the most of those cases, processing efficiency is closely related to several issues among which are:
- Data nature: including data complexity, data quality and data representative features.

- Processing technique related issues: including model choice, processing complexity and intrinsic processing delay.

One of the key points on which one can act is the complexity reduction. It concerns not only the problem solution level but also appears at processing procedure level. An issue could be model complexity reduction by splitting a complex problem into a set of simpler problems: multi-modelling where a set of simple models is used to sculpt a complex behaviour ([4] & [5]). Another promising approach to reduce complexity takes advantage from hybridization [17].
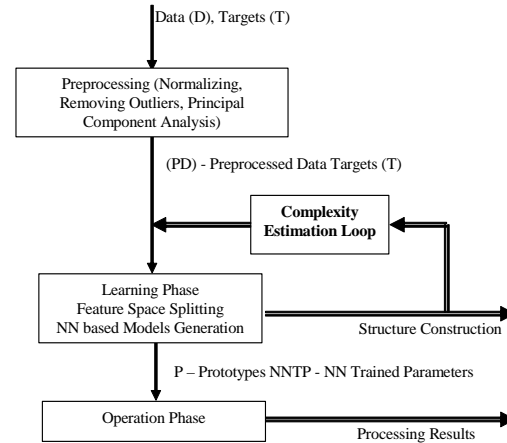

Fig. 6. General bloc diagram of DTS, presenting main operation levels.

The T-DTS includes two main operation modes. The first is the learning phase, when T-DTS system decomposes the input data and provides processing sub-structures and tools for decomposed sets of data. The second phase is the operation phase (usage the system to process unlearned data). There could be also a pre-processing phase at the beginning, which arranges (prepare) data to be processed. Pre-processing phase could include several steps (conventional or neural stages). Figure 6 gives the general bloc diagram of T-DTS operational steps. As shows this figure, T-DTS could be characterized by three main operations: "data pre-processing", "learning process" and "generalization process" (or "working process").

We designed and implemented an ANN based data driven treelike Multiple Model generator, that we called T-DTS (Treelike Divide To Simplify), able to reduce complexity on both data and processing chain levels ([19], [4], [5]). T-DTS and associated algorithm construct a tree-like evolutionary neural architecture automatically where nodes, called also "Splitting Units" (SU), are decision units, and leafs, called also "Neural Network based Models" (NNM), correspond to neural based processing units.

The learning phase is an important phase during which T-DTS performs several key operations: splitting the learning database into several sub-databases, constructing (dynamically) a treelike Supervision/Scheduling Unit (SSU) and building a set of sub-models (NNM) corresponding to each sub-database. Figure 7 represents

the division and NNM construction process bloc diagrams. As this figure shows, after the learning phase, a set of neural network based models (trained from sub-databases) are available and cover (model) the behaviour region-by-region in the problem's feature space. In this way, a complex problem is decomposed recursively into a set of simpler sub-problems: the initial feature space is divided into M sub-spaces. For each subspace k, T-DTS constructs a neural based model describing the relations between inputs and outputs. If a neural based model cannot be built for an obtained sub-database, then, a new decomposition will be performed on the concerned sub-space, dividing it into several other sub-spaces.
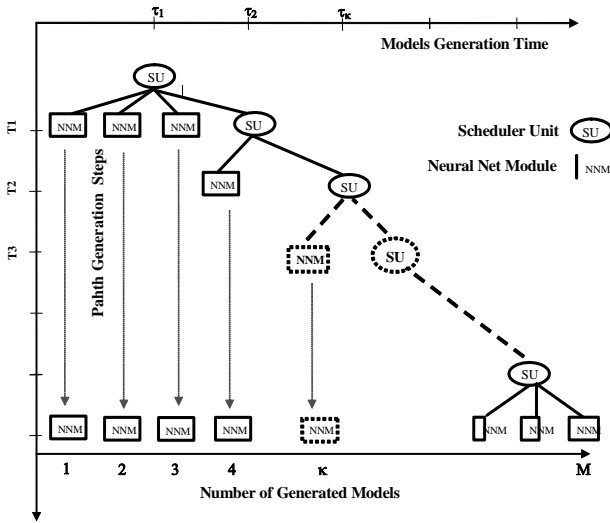
Fig. 7. General bloc diagram of T-DTS learning phase and its tree-like splitting process.

Very promising results, obtained for different areas: classification problems, industrial process identification and prediction, pattern (biomedical signal) recognition, etc… show efficiency of such self-organizing multiple model structure.

5. BIPED ROBOT'S ADAPTIVE WALK USING INTUITIVE HYBRID MODULAR CONTROLLER

One of the most challenging topics, over the recent decades, in the field of robotics concerned the design and the control of biped robots. Several potentialities make this foremost research area particularly appealing in the frame of middle and long term projection. On the fundamental side, advances in this research area can lead to a better comprehension of the human locomotion mechanisms. From, the applicative point of view, it could concern a wide spectrum of applications among which: the design of more efficient prosthesis and the construction of more sophisticated humanoid robots for interventions in hostile environments.

Two main control strategies are generally used in the field of biped robots' locomotion: one is based on a kinematics and dynamic modeling of the whole robot's mechanical structure, and another takes advantage from soft-computing techniques (fuzzy logic, neural networks, genetic algorithm, etc…) and heuristically established

rules resulting from the expertise of the walking human. Additionally to requirements related to high precision measurement and to a fine interaction forces' evaluation, the first strategy needs the modeling of whole biped robot's real environment remaining a very complex task. That is why the computing of the on-line trajectories are generally performed using simplified models ([20] to [23]), making this first strategy not always well adapted when biped robot moves in real environment. Taking advantages from soft-computing skills, the second solution doesn't need the aforementioned requirements: firstly, it is not necessary to know perfectly the mechanical structure and secondly, this category of techniques takes advantage from learning capabilities ([20] to [24]).

Investigating soft-computing based fully autonomous biped robot's walking, we proposed a new approach taking advantage simultaneously from local and global generalization. Our approach [25] is based on a modular Fuzzy-CMAC architecture: a set of CMAC ANN (see [26] to [28]) based modules and a fusion stage. The fusion is carried out by using Takagi-Sugeno FIS (Fuzzy Inference System). The main task of Fuzzy-CMAC based modular part of the system is to compute the swing leg's trajectory (using a Fuzzy Inference System fusion of several CMAC neural networks' outputs). The second one allows regulating the average velocity from a modification of the desired pitch angle at each new step. Figure 8 gives the bloc diagram of the proposed hybrid architecture.
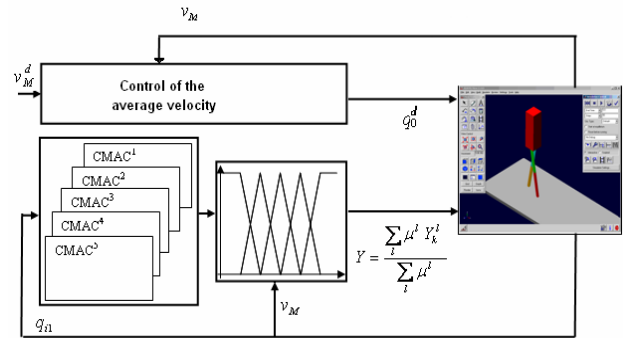
Fig.8 – Bloc- diagram of the Fuzzy-CMAC based hybrid control strategy.
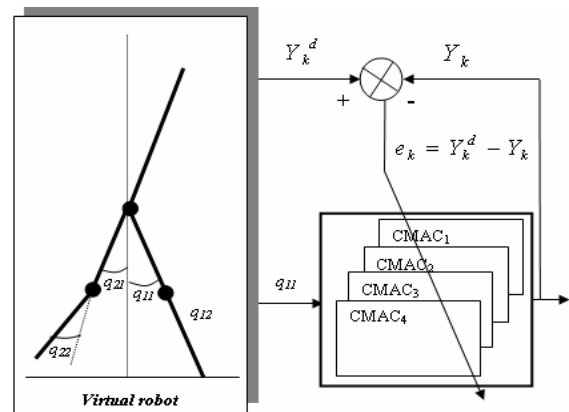
Fig. 9 – Learning strategy principle's bloc diagram.

Figure 9 shows the bloc diagram of the training strategy. The trajectories of the swing leg (in terms of

joint positions and velocities) are learned by four "single-input/single-output" $CMAC_k$ with k=1,..,4 neural networks (four trajectories to learn). The learned trajectories are joint angles q_{i1} and q_{i2}, and the two corresponding angular velocities $\dot{q}_{i1}$ and $\dot{q}_{i2}$. q_{i1} and q_{i2} are respectively the measured angles at the hip and the knee of the leg i. In the same way, $\dot{q}_{i1}$ and $\dot{q}_{i2}$ are respectively the measured angular velocities at the hip and the knee of the leg i (see figure 8). During the training stage, five trajectories corresponding to five different average velocity values (V_M measured in m/s) included in [0.4 , 0.8] interval are learned by five CMAC based modules. Each module (labelled $CMAC^l$, with $l \in \{1, 2, 3, 4, 5\}$) includes four $CMAC_k$ neural networks (corresponding to the four above-mentioned robot's trajectories). V_M is computed by using relation (6) where L_{step} is the distance between the two feet at the moment of double impact and t_{step} is the duration of the step (from takeoff to landing of the same leg).

$$V_M = \frac{L_{step}}{t_{step}} \qquad (6)$$

The Fuzzy Inference System is obtained from the five following rules, where Y^l corresponds to the output of $CMAC^l$ with $l \in \{1, 2, 3, 4, 5\}$:

- IF V_M IS VerySmall THEN $Y = Y^1$
- IF V_M IS Small THEN $Y = Y^2$
- IF V_M IS Medium THEN $Y = Y^3$
- IF V_M IS Big THEN $Y = Y^4$
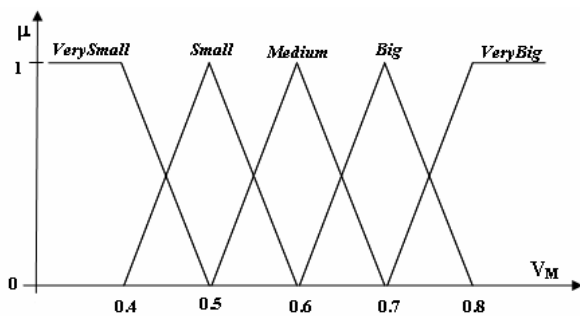- IF V_M IS VeryBig THEN $Y = Y^5$

Fig. 10 – Membership functions used by Fuzzy Inference stage of Fuzzy-CMAC.

Figure 10 gives the membership functions corresponding to the upper-indicated FIS rules. The average velocity is modelled by five fuzzy sets ("VerySmall", "Small", "Medium", "Big", "VeryBig").

The validation of proposed approach has been done on an under-actuated robot: RABBIT [29], [30]. This robot constitutes the central point of a project, within the framework of CNRS (Centre Nationale de la Recherche

Scientifique) ROBEA (ROBotique et Entité Artificielle) program [31], concerning the control of walking and running biped robots, involving several French laboratories. This robot is composed of two legs and a trunk and has no foot as shown on figure 11. The characteristics (masses and lengths of the limbs) of this biped robot are summarized in table 1.

Fig.11 – RABBIT prototype's photograph.

Table 1. Masses and lengths of the robot's limbs

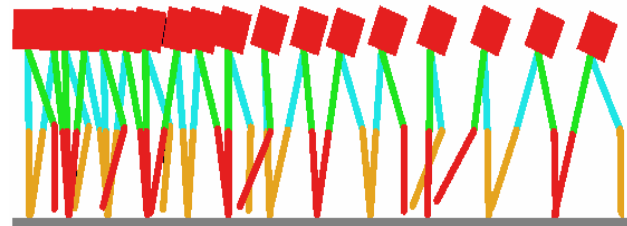| Limb	Weight (kg)	Length (m)
Trunk	12	0.2
Thigh	6.8	0.4
Shin	3.2	0.4

Fig. 12 – Stick diagram showing a walking sequence of the biped robot with increasing average velocity increases.

If it is true, from design point of view, that RABBIT is simpler compared to a robot with feet, from the control theory point of view, the control of this robot is a more challenging task, particularly because, in phase of single support, the robot is under-actuated. A numerical model of the previously described robot has been implemented within the ADAMS software. This software is able to simulate RABBIT's dynamic behavior and namely to calculate the absolute motions of the platform and the relative motions of the limbs when torques are applied on the joints by the virtual actuators. The model used to simulate the interaction between feet and ground is exposed in [32]. Figure 12 gives the stick diagram of the

biped robot's walking sequence when the desired average velocity increases. It must be noticed that the control strategy allows adapting automatically the pitch angle and the step length as the human being.

The main interest of this approach is to proffer to the walking robot autonomy and robustness. The obtained results show the adaptability of the walking step length. Furthermore, the Fuzzy-CMAC approach allows decreasing the memory size in comparison to the traditional multi-input CMAC ANN. Future works will focus firstly on the extension of the Fuzzy-CMAC approach in order to increase the autonomy of the walking robot according to the nature of the environment (get up and down stairs for instance), avoidance and dynamic crossing obstacles and secondly on the experimental validation of our approach.

6. SELF-ORGANIZING IDENTIFICATION OF NONLINEAR DYNAMIC SYSTEMS' BEHAVIOR

Identification of nonlinear systems behavior is an important task in a large number of areas dealing with real world requirements and issued applications. Among numerous areas concerned by this task, one can mention model based control and regulation, systems design, complex systems simulation, complex systems' behavior prediction, fault diagnosis, etc... The identification task involves two essential steps: structure selection and parameter estimation. These two steps are linked and generally have to be performed in order to achieve the best compromise between the identification (or prediction) error minimization and the number of parameters increase in the issued model. In real world applications (real world situations), strong nonlinearity and large number of related parameters make the realization of those steps challenging, and so, the identification task difficult.

To overcome the above-mentioned difficulties, we propose to take advantage simultaneously from multi-modeling concept's modularity (described in section 2) and self-organizing clusters construction, making the proposed solution self-adaptive regarding the system's (nonlinear system to be identified) nonlinearity. Concerning the self-organization, the proposed identifier benefits from a self-organizing clusters construction, based on concurrent minimization of both identification error and number of local models. Regarding partitioning strategy, two promising partitioning strategies have been investigated: "decision tree construction" (DTC - a deterministic partitioning approach) and "fuzzy clustering" (FC – a fuzzy based partitioning approach [33]).

The identification is performed by an "Equation Error" (EE) multi-model, known also as NARX (Nonlinear Autoregressive with eXogenous Inputs) multi-model, using "decision tree construction" or "fuzzy clustering" partitioning to split the system's feature space in a number of operating ranges [34]. Figure 13 shows the bloc diagram of an EE multi-model based identifier. As one could remark from this figure, the EE multi-model based identifier identifies the system by using both system's inputs and outputs.
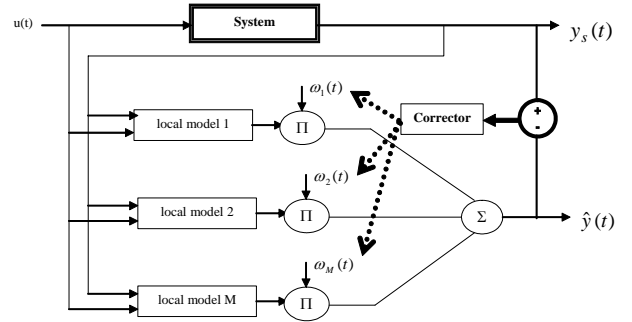

Fig. 13 – Learning bloc diagrams of EE multi-model.

In the case of a deterministic partitioning strategy, the "activation degree" of the i-th local model is defined conformably to the relation (7), where $\rho_i(.)$, called the "validity function" of the the i-th local model, is defined by the relation (8). In relation (8), $\mu_k(.)$ represents the "membership function" defined for the k-th variable of the regression vector $\varphi(t)$ and Q is the number of variables in the regression vector. In our approach, we use Gaussian membership functions expressed in (9), where: $z_{ki}(t)$ is the value of the k-th variable of the regression vector $\varphi(t)$ involved in the i-th local model, c_{ki} is the center of the partition corresponding to the $z_{ki}(t)$ and σ_k is the dispersion of the Gaussians for all partitions of the k-th variable. It is interesting to note that the parameters vector β_i contains all the dispersion of the Gaussians.

$$\omega_i(\varphi(t),\beta) = \frac{\rho_i(\varphi(t),\beta_i)}{\sum_{j=1}^{M} \rho_j(\varphi(t),\beta_j)} \quad (7)$$

$$\rho_i(\varphi(t),\beta_i) = \prod_{k=1}^{Q} \mu_k(z_{ki}(t)) \quad (8)$$

$$\mu_k(z_{ki}(t)) = \exp\left(-\frac{(z_{ki}(t)-c_{ki})^2}{2\sigma_k^2}\right) \quad (9)$$

The FC partitioning strategy uses the "fuzzy-c-mean" clustering algorithm. Conformably to the fuzzy nature of the clustering, the issued intervals (operating ranges) could share some overlapping region (with different membership degree). Feature space decomposition is performed in each dimension (for each input variable) according to concurrent minimization of both identification error and "intra-clusters" error defined by relation (10), where d_{ij} expressed by relation (11) denotes the distance between the j-th value of the variable z (which could take Q different values) and the center c_i of the i-th cluster (among M possible clusters). μ_{ij} in relation (10) represents the membership degree relative to the variable z regarding the i-th cluster (among M possible clusters), defined by relation (12). The "activation

degree" is the given by the values of μ_{ij}. The center c_i of the i-th cluster is defined conformably to the relation (13). Finally, the parameter m, known as "fuzzy exponent", is a parameter representing overlapping shapes between clusters. Generally, this parameter is set to m=2. But in our solution the value of this parameter will be optimized during the multi-model's self-organization process (learning process).

$$J(c_1, c_2, ..., c_M) = \sum_{i=1}^{M} \sum_{j=1}^{Q} \mu_{ij}^{m} d_{ij}^{2} \qquad (6)$$

$$d_{ij} = \left\| z_j - c_i \right\| \qquad (7)$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{P} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \qquad (8)$$

$$c_i = \frac{\sum_{j=1}^{Q} \mu_{ij}^{m} x_j}{\sum_{j=1}^{Q} \mu_{ij}^{m}} \qquad (9)$$

7. CONCLUSIONS

If learning and generalization capabilities of ANN models appear as central requirements in intelligent systems' design, nowadays, it is well admitted that intelligent behavior requires more sophisticated mechanisms than those performed by these "simple" models.

On the other hand, a number of appealing features of animal's and human's brain, as its "modular" structure and it's "self-organizing" capabilities, could be sources of inspiration in emergence of higher level artificial intelligent behavior. The main goal of this paper was to show how these primary supplies could be exploited or combined in the frame of "soft-computing" in order to design intelligent artificial systems emerging higher level intelligent behavior than conventional ANN. These foremost features have inspired a set of implementations dealing with real-world applications and covering several different areas as: robotics, image processing and pattern recognition, classification and dynamic nonlinear behavior modeling (identification and prediction). The presented examples and issued results show the significant potentiality of modular connectionist architectures for designing higher level intelligent functions.

8. ACKNOWLEDGEMENTS

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