Hardware Oriented Semistate Descriptions of Functional Artificial Neural Networks

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Abstract

Three hardware oriented semistate descriptions for the *Functional Artificial Neural Network* (FANN) are introduced to pave the way for VLSI realization. The first one is current-mode based in order to use current mirrors, current multipliers and integrators/differentiators. Next we show a voltage-current mixed-mode one realizable with OTAs, and finally one with all voltage variables realizable through differential operational amplifiers, etc. The functional artificial neural network under consideration uses neurons which are functionals. The Fock space in which these neurons are represented by Volterra functionals is a reproducing kernel Hilbert space, with synaptic weights as functions themselves as introduced by deFigueiredo and his students. This functional neural network can capture the dynamics present in real-world (continuous-time-parameter) nonlinear systems, enabling it to model them, as well as simulate their behavior in a computer-based environment.

1. Introduction

Neural networks [1] have the potential for very complicated behavior and their ability to learn is one of their main advantages over traditional nonlinear system. The massive interconnections of the single processing units (*neurons*) in multilayer networks provide the tool for neural network models. Their significant fault tolerance and the capability for parallel processing were the initial impetus for interest in neural netwoks. Neural networks are currently used for pattern recognition [2] and fuzzy logic [3] as well as in control [4]. In all of these areas, improvement could possibly be made by working with functionals.

The analog functional artificial neural network (FANN) [5], [6], is based on a generic two-hidden layer feedforward functional neural network architecture which processes functions instead of point evaluations of functions. It uses neurons which are functionals and is based upon the techniques of system identification introduced by Zyla and deFigueiredo [7]. These neurons are represented by Volterra functionals in Fock space, which is a reproducing kernel Hilbert space, with synaptic weights as functions themselves. Since a FANN can learn under supervision mappings of functions to functions, as compared to just mappings of points to points with conventional multilayer perceptrons, it can be used in applications such as *planning* [8] where a sequence of input events map to a sequence of output actions and in *inverse systems* [9] where the approach of hiding and retrieving information using FANNs can be used in matched transmitter and receiver pairs where both are nonlinear dynamic systems, the former encoding the information (ANN signals) using a *forward* FANN system and the latter decoding it through an *inverse* FANN system.

In an effort to find an easier way for VLSI realization [12] of the FANN than the direct realization of the following equation (2), semistate theory is employed to get it's hardware oriented semistate description. The FANN implements an operator that is a Hilbert space map, taken here to be an L_2 interpolation map of an input

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function $u(\cdot)$ into another output function $y(\cdot)$. According to Eq. (2), shown in the next section, various subsystems can be isolated so that standard subsystems e.g. multipliers [13], integrators [12], differenriators [14] and amplifiers [12], can be constructed and then combined to obtain a full system, and hence, be amenable to a semistate description useful for interconnections. Also for inverse systems, where the input to the forward FANN can be retrieved via the output of the inverse FANN, the semistate description seems to be the most suitable for deriving the inverse. Consequently, we develop the semistate description of the FANN. However, because sometimes the realization may be via currents while at other times be via voltages, we give three different sets of equations describing the FANN. In the end this paper gives a formulation suitable for VLSI realizable design for analog functional artificial neural networks (FANNs).

2. The Functional Artificial Neural Network(FANN)

For linear time-invariant systems, system identification can be accomplished with an input-output(I/O) map rather than input-output data values. This I/O map can be specified by the transfer function, or equivalently through the impulse response function which is the kernel of the convolution functional that maps input to output. Then most problems of system identification become those of identifying functional maps. Fortunately, all useful linear time-invariant continuous systems can be characterized by the convolution functionals, represented by their kernels. However, the situation becomes much more complex when we turn to nonlinear systems; still a Volterra functional representation of a system, in an abstract treatment, can be achieved, though an infinite number of power series terms are required even for simple nonlinearities. Therefore, Volterra series mappings, V, of input functions $u = u(\cdot)$ into output functions $y = y(\cdot)$ are assumed here. The input-output relation $y(\cdot) = V.(u(\cdot))$ is evaluated at time t in a real-time identification Interval I and described by a Volterra series

$$\begin{aligned} y(t) &= V_t(u(\cdot)) \\ &= \sum_{k=0}^{\infty} \frac{1}{k!} \int_I \cdots \int_I h_k(t; t_1, \cdots, t_k) u(t_1) \\ &\quad \cdots u(t_k) dt_1 \cdots dt_k \end{aligned} \tag{1}$$

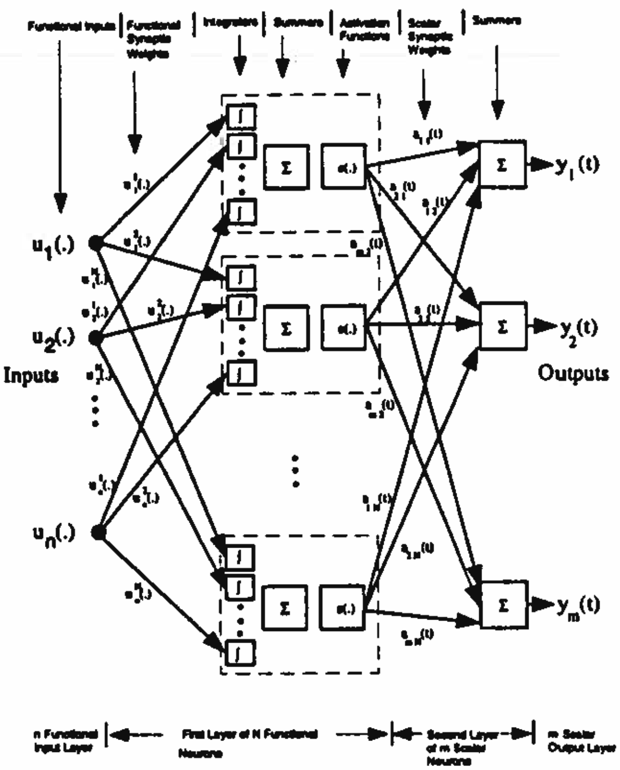

Fig. 1: Analog FANN for multiple inputs - multiple outputs

where the h_k are the kernels which charaterize the Volterra map $V.(\cdot)$ and are k-(multi)linear maps defined on the inputs as shown by the integrals. The theory for system identification via Volterra functionals in a Fock space was introduced by deFigueiredo and is presented in [6], [7], [10], [11]. An optimal interpolation using such Volterra functionals is given in [7] as

$$y(t) = V_t(u(\cdot)) = \sum_{j=1}^{N} a_{[j]}(t)\, e^{\left(\frac{1}{r} \int_I u^{(j)T}(\tau) \cdot u(\tau) d\tau\right)} \tag{2}$$

where the inputs $u(t)$ and outputs $y(t)$ are vectors of real values at time t, and where the vector function $u(\cdot)$ consists of n components and $y(\cdot)$ consists of m components, and N is number of exemplars, resulting in a real multiple-input multiple-output functional artificial neural network as shown in figure 1. Functional artificial neural networks (FANNs) implement this optimal Fock space map of an input in $L_2(I)$, defined in an interval I, into an output, where the Fock space is designated as $F_r(L_2(I))$, with the r of Eq. (2) a positive constant [7]. Learning takes place through specifying the reproducing kernels in nonlinear Volterra functionals. This requires to solve the minimum norm problem in a Bochner space related to the Fock space to which the L_2 Volterra functionals belong. In the implementation of a FANN, inputs are considered as functions $u(\cdot)$ and outputs as functions $y(\cdot)$. An analog FANN implements operators that are optimal $F_r(L_2(I))$ interpolation maps [10] of the continuous input functions, based on equation (2). A FANN is trained with exemplar input-output pairs by setting the vector weights $a_{[j]}(\cdot)$, which are also functions. System identification may be performed with a FANN by associating it with a Volterra functional input-output map.

A problem of physical realizability occurs in implementing equation (2), since the integrals use signals over future time. We circumvent this by adapting the theory to the hardware of FANNs, by assuming that t is the end point of I. Then I may be chosen as $I = I_t = [0, t]$, thus allowing to use real capacitors to perform the integration. Forming a running interval I_t for the integration over all used time, allows us to overcome the problem of handling future signals, where integration needs also to be performed, in real time.

3. The FANN Semistate Equations

The semistate descriptions of the FANN are based on the work of Newcomb and Dziurla [15]. Systems theory allows us to describe a system's operation in terms of the description of subsytems which when connected comprise the entire system. These subsystems in turn are composed of basic components which are either dynamic or static. These components are usually described in terms of either differential or algebraic equations. The overall system, after putting its subsytems together following the particular system's connection laws, is described in a mixed differential-algebraic form. In many cases a state-variable description is employed in order to model a system but in some cases, when subsystems having a state-variable description are put together, the overall system description may not have a state-variable description. In such cases semistate-variable description can be used. Canonical semistate equations are equations of the form

$$E\dot{x} = A(x,t) + Bu \qquad (3)$$

$$y = Cx \qquad (4)$$

where x is the semistate k - vector, u is the input n - vector, y is the output m - vector, and E, B, C are constant matrices; A is a mapping which includes the nonlinearities and explicit time variations of the system, and in the case of a linear time-invariant system is given in terms of a constant matrix $\hat{A}$ as Ax. When dealing with physical systems, as it is assumed here, all the quantities involved are real-valued, but the theory is not limited by such an assumption [?].

First we consider the implementation of a FANN in the context of mathematical variables. The patterns $u^{[j]}(\cdot)$, $\{1 \le j \le N\}$ are used as exemplar inputs for training the network under supervision. Each $u^{[j]}(t)$ also acts as a vector of n synaptic weights, at time t, in the first of the two hidden layers of the FANN. Similarly $a_{[j]}(t)$ is a vector of m synaptic weights at t in the second layer of the FANN. During training of the FANN the $a_{[j]}(t)$ are calculated as vector valued functions of t. When an unknown pattern $u(\cdot)$ is presented to a FANN, it determines the similarity of this pattern to each of the exemplars $u^{[j]}(\cdot)$ and estimates $y(\cdot)$ through weighted averaging of high selectivity over the corresponding exemplar outputs $y_{[j]}(\cdot)$, where the degree of selectivity may be adjusted through r. Therefore, if pattern $u(\cdot)$ is very alike to $u^{[k]}(\cdot)$ and much different from all other exemplars $u^{[l]}(\cdot)$, then $y(\cdot)$ is approximated by $y_{[k]}(\cdot)$. Next we illustrate how this framework in terms of mathematical variables can be transformed to physical quantities (currents or voltages) in order to achieve a VLSI hardware realization of a FANN which appears to be feasible through any one of its three different semistate descriptions.

In equation (2), updated by using $I = I_t = [0, t]$, we can transform the mathematical variables in terms of currents or voltages in the following manner.

We have

$$y(t) = \sum_{j=1}^{N} a_{[j]}(t) e^{\left(\frac{1}{r}\int_0^t u^{[j]T}(\tau)u(\tau)d\tau\right)} = \sum_{j=1}^{N} y_{[j]}(t) \qquad (2)$$

in which we set

$$y(t) = i_y(t) \quad or \quad v_y(t) \qquad (5\text{ a,b})$$

to get either

$$i_y(t) = \sum_{j=1}^{N} i_{y_{[j]}}(t) \quad or \quad v_y(t) = \sum_{j=1}^{N} v_{y_{[j]}}(t) \qquad (6\text{ a,b})$$

Also we will set for the input

$$u(t) = i_u(t) \quad or \quad v_u(t) \qquad (7\ a,b)$$

and coefficients as

$$a_{[j]}(t) = i_{a_{[j]}}(t) \quad or \quad v_{a_{[j]}}(t); \quad \{1 \le j \le N\} \qquad (8\ a,b)$$

For the exemplars we set

$$u^{[j]}(t) = i_u^{[j]}(t) \quad or \quad v_u^{[j]}(t); \quad \{1 \le j \le N\} \qquad (9\ a,b)$$

For the conversion constant we define three different forms used in current-mode, voltage-current mixed mode and voltage mode respectively as

$$\frac{1}{r} = \frac{R_a}{V_T} \times \frac{1}{RC} \times \frac{K}{I_b} \quad or \quad \frac{R_a}{V_T} \times \frac{1}{RC} \times K_m \quad or \quad \frac{1}{V_T} \times \frac{1}{RC} \times K_m \qquad (10\ a,b,c)$$

where R_a is an internal resistor in an exponential amplifier, $V_T = \frac{kT}{q}$ is the thermal voltage at temperature T ($V_T = 26mV$ at $300\ K$), RC is integration constant, K and I_b are a scale factor and an internal biasing current, respectively, in current multipliers and K_m is a voltage multiplier's scale factor.

3.1. Current-mode Semistate description of FANN

In the first case we consider all the semistate variables of the FANN as the currents set above. This current-mode realization can be acheived by employing analog building blocks such as current mirrors, current multipliers, exponential amplifiers and integrators. Thus, the equation (2) is rewritten as

$$\begin{aligned} i_y(t) &= \sum_{j=1}^{N} i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} \times \frac{1}{RC} \times \frac{K}{I_b} \int_0^t i_u^{[j]T}(\tau) i_u(\tau) d\tau\right)} \\ &= \sum_{j=1}^{N} i_{y_{[j]}}(t) \end{aligned} \qquad (11\ a)$$

where

$$i_{y_{[j]}}(t) = i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} i_{z_1}^{[j]}(t)\right)} \qquad (11\ b)$$

Let us consider now the set of semistates i_{z_1}, i_{z_2} and i_{z_3} defined as:

$$i_{z_1}^{[j]}(t) = \frac{1}{RC} \times \frac{K}{I_b} \int_0^t i_u^{[j]^T}(\tau) i_u(\tau) d\tau \qquad (12\ a)$$

$$i_{z_2}(t) = i_u(t) \qquad (12\ b)$$

$$i_{z_3}(t) = \sum_{j=1}^{N} i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} \times \frac{1}{RC} \times \frac{K}{I_b} \int_0^t i_u^{[j]T}(\tau) i_{z_2}(\tau) d\tau\right)} \qquad (12\ c)$$

$$= i_y(t) \qquad (13)$$

We also use the following notation for the associated vectors, with column index $1 \le j \le N$,

$$\begin{aligned} i_{z_1}^{[\cdot]}(t) &= \left[i_{z_1}^{[j]}(t) \right] \\ f(i_{z_1}^{[\cdot]}(t)) &= \sum_{j=1}^{N} i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} i_{z_1}^{[j]}(t)\right)} \\ i_u^{[\cdot]}(t) &= \left[i_u^{[1]}(t), i_u^{[2]}(t) \dots i_u^{[N]}(t) \right] \end{aligned} \qquad (14\ a,b,c)$$

Note that $i_{z_1}^{[\cdot]}$ is an N - vector, $f(i_{z_1}^{[\cdot]})$ is an m - vector and $i_u^{[\cdot]}$ is an n - vector.
We define the semistate as the $(N+n+m)$ - vector

$$i_z = \begin{bmatrix} i_{z_1}^{[\cdot]} \\ i_{z_2} \\ i_{z_3} \end{bmatrix} \qquad (15)$$

On differentiating equation (12a), in matrix form equations (12) give the normalized semistate equations

$$\begin{bmatrix} 1_N & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \bullet \frac{di_z}{dt} = \begin{bmatrix} 0_N & i_u^{[\cdot]^T} & 0 \\ 0 & -1_n & 0 \\ 0 & 0 & -1_m \end{bmatrix} \bullet i_z + \begin{bmatrix} 0 \\ 0 \\ f(i_{z_1}^{[\cdot]}) \end{bmatrix} + \begin{bmatrix} 0 \\ 1_n \\ 0 \end{bmatrix} \bullet i_u \qquad (16)$$

$$i_y = \begin{bmatrix} 0 & 0 & 1_m \end{bmatrix} \bullet i_z \qquad (17)$$

Here the E matrix has been normalized to the identity direct sum zero.

3.2. Voltage-Current mixed-mode Semistate description of FANN

Here, in this second voltage-current mixed-mode semistate description of FANN, we consider both voltages and currents as semistate variables. This form of FANN can be realized using operational tranconductance amplifiers (OTAs). In this case, equation (2) can be rewritten as

$$\begin{aligned} i_y(t) &= \sum_{j=1}^{N} i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} \times \frac{1}{RC} \times K_m \int_0^t v_u^{[j]T}(\tau) v_u(\tau) d\tau\right)} \\ &= \sum_{j=1}^{N} i_{y_{[j]}}(t) \end{aligned} \quad (18\text{ a})$$

where

$$i_{y_{[j]}}(t) = i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} i_{x_1}^{[j]}(t)\right)} \quad (18\text{ b})$$

We set

$$i_{x_1}^{[j]}(t) = \frac{1}{RC} \times K_m \int_0^t v_u^{[j]T}(\tau) v_u(\tau) d\tau \quad (19\text{ a})$$

$$v_{x_2}(t) = v_u(t) \quad (19\text{ b})$$

$$i_{x_3}(t) = \sum_{j=1}^{N} i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} \times \frac{1}{RC} \times K_m \int_0^t v_u^{[j]T}(\tau) v_{x_2}(\tau) d\tau\right)} \quad (19\text{ c})$$

$$= i_y(t) \quad (20)$$

We also use the following notations, where column index $1 \leq j \leq N$,

$$\begin{aligned} i_{x_1}^{[\cdot]}(t) &= \left[i_{x_1}^{[j]}(t)\right] \\ f(i_{x_1}^{[\cdot]}(t)) &= \sum_{j=1}^{N} i_{a_{[j]}}(t) e^{\left(\frac{R_a}{V_T} i_{x_1}^{[j]}(t)\right)} \\ v_u^{[\cdot]}(t) &= \left[v_u^{[1]}(t), v_u^{[2]}(t) \ldots v_u^{[N]}(t)\right] \end{aligned} \quad (21\text{ a,b,c})$$

Note that $i_{x_1}^{[\cdot]}$ is an N - vector, $f(i_{x_1}^{[\cdot]})$ is an m - vector and $v_u^{[\cdot]}$ is an n - vector.
Here we define the semistate as the $(N+n+m)$ - vector

$$x = \begin{bmatrix} i_{x_1}^{[\cdot]} \\ v_{x_2} \\ i_{x_3} \end{bmatrix} \quad (22)$$

In Matrix form equation (19) gives the semistate equations

$$\begin{bmatrix} 1_N & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \bullet \frac{dx}{dt} = \begin{bmatrix} 0_N & v_u^{[\cdot]T} & 0 \\ 0 & -1_n & 0 \\ 0 & 0 & -1_m \end{bmatrix} \bullet x + \begin{bmatrix} 0 \\ 0 \\ f(i_{x_1}^{[\cdot]}) \end{bmatrix} + \begin{bmatrix} 0 \\ 1_n \\ 0 \end{bmatrix} \bullet v_u \quad (23)$$

$$i_y = \begin{bmatrix} 0 & 0 & 1_m \end{bmatrix} \bullet x \quad (24)$$

3.3. Voltage-mode Semistate description of FANN

Finally, we describe the all voltage variable based semistate description of the FANN in order to be realiazable through differential operational amplifiers. We can rewrite equation (2) as

$$\begin{aligned} v_y(t) &= \sum_{j=1}^{N} v_{a_{[j]}}(t) \frac{R_2}{R_1} e^{\left(\frac{1}{V_T} \times \frac{1}{RC} \times K_m \int_0^t v_u^{[j]T}(\tau) v_u(\tau) d\tau\right)} \\ &= \sum_{j=1}^{N} v_{y_{[j]}}(t) \end{aligned} \quad (25\text{ a})$$

where R_1 and R_2 are internal resistors in an exponential amplifier and

$$v_{y_{[j]}}(t) = v_{a_{[j]}}(t) \frac{R_2}{R_1} e^{\left(\frac{1}{V_T} v_{x_1}^{[j]}(t)\right)} \quad (25\text{ b})$$

In this case we set the semistate equations from

$$v_{x_1}^{[j]}(t) = \frac{1}{RC} \times K_m \int_0^t v_u^{[j]T}(\tau) v_u(\tau) d\tau \quad (26\text{ a})$$

$$v_{x_2}(t) = v_u(t) \quad (26\text{ b})$$

$$v_{x_3}(t) = \sum_{j=1}^{N} v_{a_{[j]}}(t) \frac{R_2}{R_1} e^{\left(\frac{1}{V_T} \times \frac{1}{RC} \times K_m \int_0^t v_u^{[j]T}(\tau) v_{x_2}(\tau) d\tau\right)} \quad (26\text{ c})$$

$$= v_y(t) \quad (27)$$

We also use the following notations, where column index $1 \leq j \leq N$,

$$\begin{aligned} v_{x_1}^{[\cdot]}(t) &= \left[v_{x_1}^{[j]}(t)\right] \\ f(v_{x_1}^{[\cdot]}(t)) &= \sum_{j=1}^{N} v_{a_{[j]}}(t) \frac{R_2}{R_1} e^{\left(\frac{1}{V_T} v_{x_1}^{[j]}(t)\right)} \\ v_u^{[\cdot]}(t) &= \left[v_u^{[1]}(t), v_u^{[2]}(t) \ldots v_u^{[N]}(t)\right] \end{aligned} \quad (28\text{ a,b,c})$$

Note that $v_{x_1}^{[\cdot]}$ is an N - vector, $f(v_{x_1}^{[\cdot]})$ is an m - vector and $v_u^{[\cdot]}$ is an n - vector. In Matrix form equation (26) gives the semistate equations

$$\begin{bmatrix} 1_N & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \bullet \frac{dv_z}{dt} =$$

$$\begin{bmatrix} 0_N & v_u^{[\cdot]T} & 0 \\ 0 & -1_n & 0 \\ 0 & 0 & -1_m \end{bmatrix} \bullet v_z + \begin{bmatrix} 0 \\ 0 \\ f(v_{z_1}^{[\cdot]}) \end{bmatrix} +$$

$$\begin{bmatrix} 0 \\ 1_n \\ 0 \end{bmatrix} \bullet v_u \tag{29}$$

$$v_y = \begin{bmatrix} 0 & 0 & 1_m \end{bmatrix} \bullet v_z \tag{30}$$

where the semistate is the $(N+n+m)$ - vector

$$v_z = \begin{bmatrix} v_{z_1}^{[\cdot]} \\ v_{z_2} \\ v_{z_3} \end{bmatrix} \tag{31}$$

4. Discussion

In the above we have determined three different sets of semistate equations which characterize the operation of the functional artificial neural network discussed in the paper. Although a large number of other sets are possible the ones shown are of special interest since they should lead to VLSI hardware realization through either all current-mode circuitry or voltage-current mixed-mode or just voltage based circuits. However, they do pose a number of challenges for realization in terms of electronic hardware, mostly due to the denormalizations needed and the fact that the equations involve differential equations. State variable types of equations deal with inputs and outputs and in our case we have considered cases where inputs could be in voltage or current form. In all cases the structure of the semistate equations is esentially the same with minor differences. The FANN description with semistate equations provides a formal way for its VLSI hardware design, and it is in this spirit that our equations have evolved.

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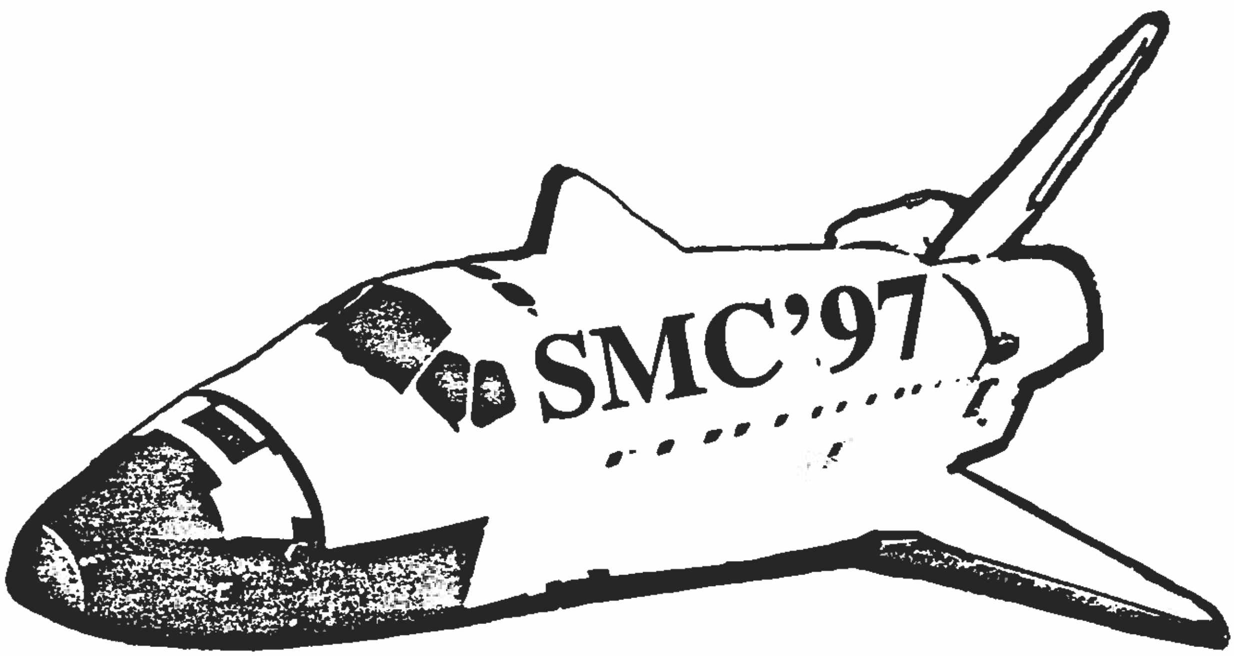

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