

# A Built-in Methodology for Resemblance Gathering in RKII Networks

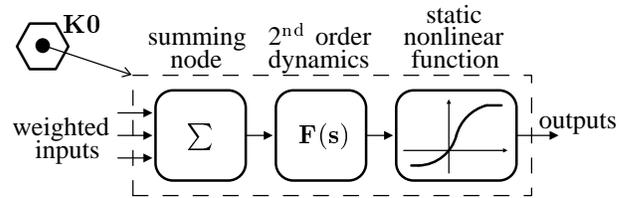
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**Abstract**—This paper presents a methodology to test RKII cells for dynamic resemblance. The cells are the basic processing blocks of RKII networks, which, as with other Artificial Neural Networks, are made of repeated processing elements interconnected in some pre-defined manner. For the RKII network, each processing element, the RKII, is a dynamic piece that behaves as an input controlled oscillator, therefore the network represents a set of coupled oscillators. Each RKII cell in the network should exhibit similar characteristics for suitable operation. However, in a real analogue CMOS VLSI implementation, similarity will change along the integrated circuit, due to process variations, failures, or even performance degradation. The variations found in different cells may prevent the network to operate properly. The present work presents a method to find and select a set of RKII cells, within the chip universe, that reflects a pre-defined degree of similitude. The method employs an iterative procedure that searches the network to find the set of cells that fit within a percentage of dynamic variation, and finds a maximum number of cells that best resemble each other. In the end, the most similar cells are selected while the others are turned off.

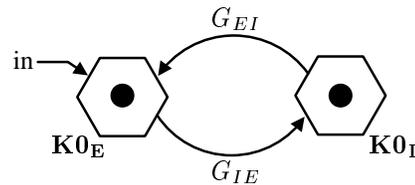
## I. INTRODUCTION

The KII model was originally proposed by Walter Freeman to explain the olfactory cortex cognitive function [1], [2]. This model has been applied to different recognition, classification and function approximation problems [3]–[5]. Freeman has proposed a level of model description that is an intermediate between global states, related to mammal’s behavior, and single neuron states. The result is a complex dynamical system built from basic second order nonlinear elements in a hierarchy of levels, called Katchalsky [1], and designated by K0, KI, KII, KIII, etc. The reduced KII (RKII) is a particular part of the full model that, when correctly parameterized, behaves as an oscillator controlled by an input. This oscillator behavior is distinct from a VCO since the frequency does not depend on the input, but solely on the system parameters. When these cells are interconnected, the network then forms a set of coupled oscillators. The inter-connectivity can be programmed, endowing the network with the ability to work as an associative memory, meaning that the coupling is related to some memorised (or trained) information. When a recognisable input is present, even if partially completed or embedded in noise, the network is capable of retrieving the correct information.

The K0 cells are the basic building block of Freeman’s networks. Each K0 is modelled by a summing input node, a second order low-pass filter and a static nonlinearity, as shown in figure 1(a). The RKII cell, represented in figure 1(b)



(a) K0 basic building block



(b) RKII model ( $G_{EI}$  and  $G_{IE}$  are interconnection gains)

Fig. 1. K0 cell and RKII model

by two K0 cells, is made-up of two K0 cells, one excitatory ( $K0_E$ ) and the other inhibitory ( $K0_I$ ). A RKII network is assembled by interconnecting a certain number of RKII cells (figure 2). The resulting network is topologically equivalent to a set of coupled oscillators. The coupling strengths can be programmed and this is the key to build-in information processing capabilities. Yet, a close observation of the model reveals a massively interconnected network. Actually, the inter-connectivity increases in the order  $O(N^2)$  being  $N$  the number of cells (RKII oscillators) in use. To overcome such complexity, a multiplexing scheme was recently proposed to down-scale this number to  $O(N)$  [6]. Nonetheless, the problem with an analogue implementation relates with the difficulty to keep the same dynamics for the different RKII in the IC. If they are too far apart in their dynamics, there is a chance for the RKII cells not to lock, preempting the network from working properly. We then propose in this paper a methodology that searches the network and finds the RKII cells that are more alike, within a predefined normalised tolerance, and disconnects all others. This methodology can be extended to other types of circuits that share the same properties, i.e., many cells that must be similar (e.g. SI filters,

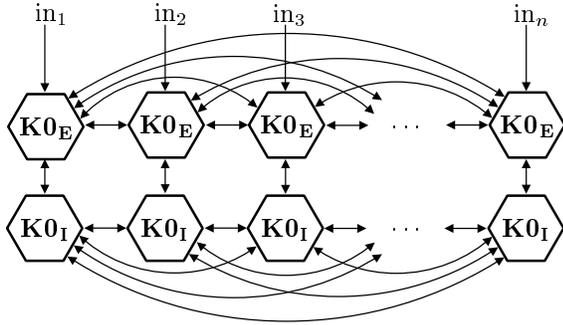


Fig. 2. RKII network

neural networks,...), both for behavior and failure. The RKII cell is composed by filter-and-hold blocks [10], multipliers, memories, average and nonlinearity cells [11]. The scheme proposed here evaluates the gain response of each RKII cell, and in order to minimise test circuitry overhead, the adopted strategy enables the comparison between two and more RKII cells by means of its own circuit blocks.

## II. BUILT-IN TEST METHOD

The built-in self testing (BIST) approach being proposed here can be included in the category of the reconfiguration based mixed-signal BIST techniques. Conceptually, it resembles those relying on the comparison of nominally identical responses provided by similar modules or cells. That is the case, e. g., with the BIST of S<sup>2</sup>I switched current circuits presented in [7], where the currents of adjacent cells are compared against each other to detect the presence of faults. Identical approaches have been developed within switched capacitor circuits. The BIST method proposed in [8] tackles the problem of testing programmable capacitor arrays using capacitor comparison techniques. A programmable reference block is used in [9] to replicate the behavior of each biquad in a filter, and obtain then a reference response against which the response of the biquad under test is compared to.

Likewise, the modularity of a structure, comprising regularly interconnected RKII cells, is explored in this work. The reference is determined by an average and not a single value or response, and in each test operation the corresponding reference average needs to be memorised. For this purpose, the testing method takes advantage of the accessible RKII analogue circuits, such as memory and multipliers. Since the proposed BIST method takes advantage of existing resources it introduces very small hardware overhead.

The absolute response of each RKII is not a critical factor; however, the relative responses are important. In order to measure the degree of similitude, one could compare pairs of cells through subtraction of their responses. Lower difference would mean close behavior. The problem is that the control of such test procedure would be too cumbersome since every pair would have to be compared. A more global approach is needed. The method we propose finds the average behavior of all cells, and then a search is made to find the closest

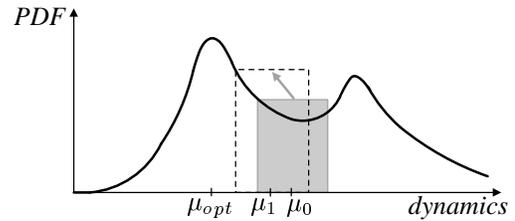


Fig. 3. Hypothetical probability density function of RKII dynamics

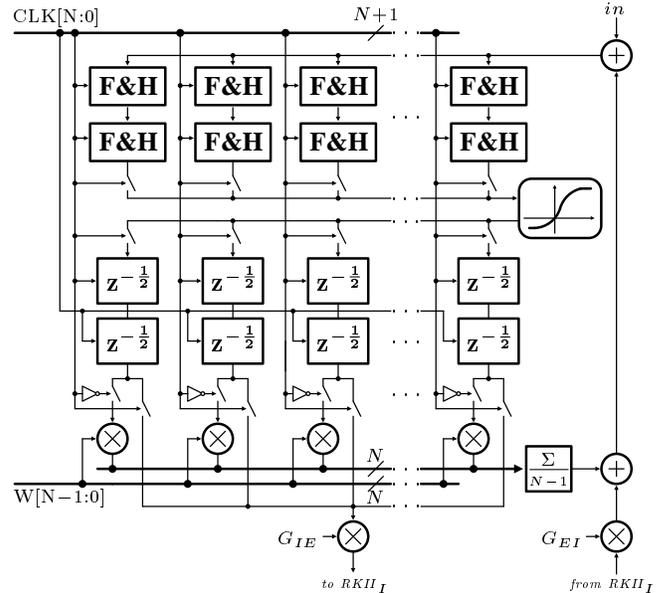


Fig. 4.  $\frac{1}{2}$  RKII network

cells to that behavior, by means of a normalised measure, e.g., a percentage interval around the average value. This, however, does not signify that the global mean value is the actual optimum value. Consider the example of the probability density function (PDF) in figure 3. This PDF represents a hypothetical distribution of dynamics for all RKII cells in an IC. Evidently, an interval around the global mean (shaded region around  $\mu_0$  in the figure) would not represent the best region, since it does not maximise the number of cells that are alike. The best regions would be those around the peaks. The idea is now to move the mean towards the maximums. This is accomplished by taking the mean of the current (shaded) interval. Since the slope is higher at the left than at the right, the new mean would move to the left, to  $\mu_1$ . The procedure is repeated, i.e., a new set of cells is found to fit within a new interval region around a new mean. New iterations will move the averages and the intervals towards the peak at  $\mu_{opt}$ , until the average rests within two consecutive iterations.

### A. Test implementation

Figure 4 presents the block diagram of a real CMOS implementation of the network shown in figure 2. Only the top row ( $K0_E$ ) is represented, the bottom row ( $K0_I$ ) is similar, except for the nonlinearities that are symmetrical. All blocks

represent actual circuits, such as, multipliers, memory cells ( $z^{-1}$ ), low-pass filters (F&H), and spatial averaging. Due to the low-pass characteristic of the RKII, a sinusoidal response will give a good guess on how well tuned the different filters are (the non-linearity is not important because it is multiplexed among all cells). For test proposes, all the RKII cells, that constitute the entire RKII network, are then initially excited by a common input sine wave. For AC coupled circuits, one cannot infer the mean by simply averaging the waveforms (the average of a sine wave is zero). Instead, the square of the signal will be used, taking advantage of an existing multiplier circuit, with two short-circuited inputs. Thus, the resulting signal has now a non-null DC value and a doubled frequency component. Applying this waveform to a time averaging circuit, the average power can be obtained for any RKII cell. This value will be stored in the memory block needed at each RKII cell and, therefore, it is available for subsequent processing during all the evaluation procedure, while the average block is free for other operations.

The cell selection method can be described as follows. The starting point is established by making use of the spatial averaging circuit applied to all memory outputs. This way, the overall response of the RKII network is obtained as an initial guess. A relative bound is established in terms of power deviation from this average value. The absolute difference between the average value (early determined) and the power average for each cell (stored in the memories) is compared to the considered deviation. This procedure provides means to deselect cells with powers out of the bounds imposed. The outputs of selected cells are averaged to find a new central point for the new interval that should be, as stated, bounded by a new maximum deviation value. This maximum deviation value is determined always as relative to the new average value. The sequential comparisons are repeated for this new iterative step where cells are selected or deselected until the RKII network is entirely swept. In terms of statistical distribution, this will correspond to a varying interval that iteratively moves towards higher slopes of concentration, as shown in figure 3. The cycled method will continue until a certain average repeats with the same value in two consecutive iterations. The presented method guarantees that the final interval is located near to a maximum of the power distribution. For Gaussian and uniform distributions (as well others with only one peak value), using very low degrees of deviation, the resultant sharp interval may lead to the high concentrations at the overall average power. The power deviation is used as a control parameter and will also influence on test duration time. In the presence of not so well behaved distributions, with more than one peak value on the power PDF, the iterative method will not necessarily converge to the best interval. However, it is assured that the final average value will always tend to a local maximum. Therefore, for typical statistical distributions, the similitude properties are secured by the present methodology for RKII networks and can even be extended to similar neural networks, or other systems, where the same procedure can be imposed by equivalent built in components.

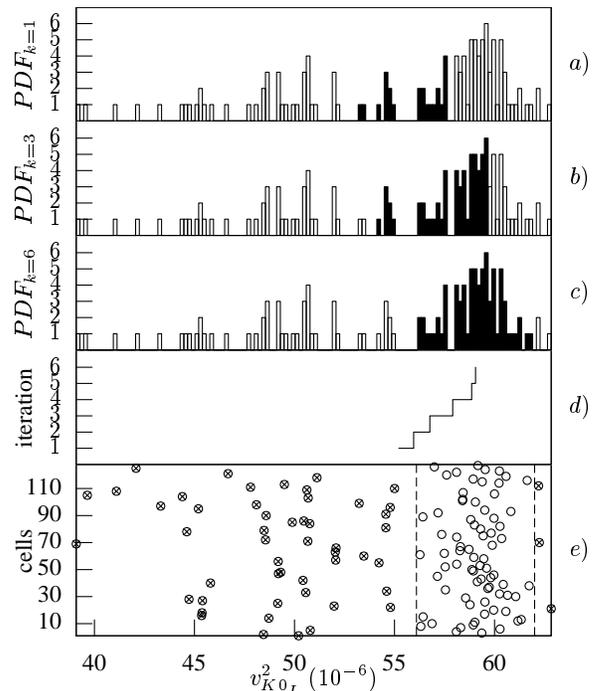


Fig. 5. Test method applied to a gaussian process of four dynamical parameters. a) to c)- Three iteration samples out of the six needed to find the solution. d)- Average evolution by iteration. e)- Final poll of cells selected as the maximum number within a given 5% variation.

### III. TEST RESULTS

Figure 5 shows a behavioural experiment with the test method applied to a network with 128 channels (inputs). It should be noted that the represented quantities refer to simulated values taken from RKII circuit models, by statistically changing the dynamical parameters of each cell. Although the number of cells considered here is not high enough to exhibit a near continuous statistical distribution, it does not invalidate the methodology here presented. The number of cells considered is due to the fact that there is a maximum limit on the number of cells allowed by multiplexed schemes. This is however similar to the most practical cases of circuits with a finite number of repeated cells. For the experiment shown in figure 5 the poles from the second order system and the gains from each multiplier were defined as independent random variables, i.e., four dynamical parameters – two from the F&Hs and the other two from multipliers in each  $K_{0E}-K_{0I}$  pair – that were randomly set using uniform and gaussian distributions. As seen in the figure, the responses of the different RKII cells in the network are well spread. One can easily identify a major concentration region of cells, away from the overall average dynamical behaviour. This would be the best set of cells to choose from. Figure 5 shows three of the six iterations that the algorithm needs to reach the final solution. On the first iteration (Figure 5-a)) the set of cells select corresponds to an interval around the overall average. With further iterations, the selected interval moves towards the main concentration region (Figures 5-b) and c)). Figure 5-d) represents the average

evolution, and Figure 5-e) shows the final universe of RKII cells selected by the algorithm as the maximum number with most resemblance in dynamics.

#### IV. CONCLUSION

This work presents a methodology to test and decide which cells are more alike within a network of repeated cells. The likeness of responses relates with parameter variations along an Integrated Circuit, but may also be due to defects. The iterative procedure proposed here is based on the comparison of individual cells dynamics. At first, the algorithm starts finding a pool of cells that show dynamic responses close to the overall average. It then begins searching in its vicinity for the maximum number of cells that match within an arbitrary interval of square magnitude deviation.

The method shows that it is capable of choosing a good pool of cells within a predefined large variance of dynamical responses. The testing procedure also uses mathematical operators that are implemented with existing circuits in the system, lowering the overhead of auxiliary circuits.

#### ACKNOWLEDGMENT

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