A Hierarchical Clustering Network Based on a Model of Olfactory Processing

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Abstract. We describe a direct analog implementation of a neural network model of olfactory processing [44-48]. This model has been shown capable of performing hierarchical clustering as a result of a coactivity-based unsupervised learning rule which is modeled after long-term synaptic potentiation. Network function is statistically based and does not require highly precise weights or other components. We present current-mode circuit designs to implement the required functions in CMOS integrated circuitry, and propose the use of floating-gate MOS transistors for modifiable, nonvolatile interconnection weights. Methods for arrangement of these weights into a sparse pseudo-random interconnection matrix, and for parallel implementation of the learning rule, are described. Test results from functional blocks on first silicon are presented. It is estimated that a network with upwards of 50K weights and with submicrosecond settling times could be built with a conventional CMOS double-poly process and die size.

1. Introduction

In recent years, interest in neural networks and neural-network-like computational models has seen a major resurgence, due at least in part to the prospect of compact and dense implementation of these networks in analog integrated circuit form. A number of widely studied architectures and algorithms are based on adaptations of conventional statistical and numerical techniques which admit parallel network implementations (e.g., multilayer perceptrons with back-propagation learning [1], learning vector quantization [2], and radial basis function or probabilistic neural networks [3, 4]), or on analogy with physical systems (e.g., Hopfield networks [5] and Boltzmann machines [6]). These might be properly termed artificial neural network algorithms, with emphasis on the artificiality, since resemblance to real neural networks (beyond the parallel structure of interconnected processing units) is likely to be either superficial or coincidental. These algorithms have been applied with some success to a number of problems, although studies of them have been conducted almost exclusively in simulations. Much debate has centered on the relative advantages, and even feasibility, of analog versus digital implementations [7, 8]. With the architectures and algorithms that are commonly reported, the precision with which interconnection weights can be represented and the resolution of weight changes during learning are important issues in both the digital and analog cases.

Elucidation of the computational principles used in real nervous systems, on the other hand, has been very limited due to the extreme experimental difficulties encountered in network neuroscience. Understanding of collective function of neural networks in vertebrates is largely limited to sensory structures and early processing, which have been studied in the greatest depth and with the most success; even in these cases, interpretation of the computational principles which are followed is a matter of current research [9-11].

A number of the direct analog implementations of neural networks that have been reported to date consist of building blocks that are suitable for the artificial paradigms; the layered heavily interconnected feedforward architecture epitomized by the multilayer perceptron [12-18] or the reciprocally and symmetrically interconnected architecture described by Hopfield [5] and Cohen and Grossberg [19] are often targeted [20-22]. By way of contrast, some researchers, most notably Mead and co-workers, have attempted to build reasonably faithful analogs of biological neurons or networks [23-29], which are generally early processing structures for sensory input. Mueller and co-workers have reported an intermediate approach with a chipset retaining some notable features of biological neurons but allowing programmable interconnection into general networks [30].
An outstanding problem in analog networks is the practical implementation of learning, which in the neural network field usually comprises some algorithmic procedure for modification of interconnection weights between neuronal analogs in response to stimuli and possibly desired response or other feedback presented to the network. Few implementations reported to date actually include learning of this kind on chip [17, 20, 22]. Implementations of biologically inspired networks are often hardwired [24-26], although a few models with limited adaptive capabilities have been built [27, 28]. A central research issue for implementation of the artificial learning paradigms is the precision with which weight or other parameter changes may be calculated (dependent upon precision of components such as weight circuits) and imposed. A suitable analog medium for long-term storage of weights or other parameters is also a matter of current research; floating-gate MOS or MNOS devices have been proposed for this purpose, and studied by a number of workers [12, 27, 31-36]. The potential due to the charge stored on such a structure could be used to control the conductance of a transistor or transistors in a circuit performing the weighting function. However, the processes by which the stored charge may be altered require either UV irrigation, or high programming voltages to induce Fowler-Nordheim tunneling or hot-carrier injection. In the latter cases particularly, the charging phenomena are very nonlinear and sensitive to geometries and processing parameters [37], and thus it is difficult to conceive of precise modification of analog weights without some kind of local closed-loop control. A few workers have proposed modifications of established algorithms, such as very coarse quantization of weight updates [38, 39], which circumvent the need for imposition of precise weight changes, but the practicability of implementing even these learning rules in parallel in analog circuitry remains to be demonstrated.

In biological neural networks, modulation of synaptic efficacy has long been regarded as a likely mechanism for learning and memory [40], and the phenomenon of long-term potentiation (LTP) as observed in the hippocampus, limbic system, and certain cortical structures is one candidate for this type of mechanism [41-43]. Changes in synaptic strength due to LTP are thought to be rather coarse [43], in contrast with the graded and precise weights and weight changes which are required by the artificial paradigms. How a nervous system might work within such constraints to perform useful computation and to learn effectively is a question whose resolution is stymied by the paucity of information on network-level function within the brain. However, a potentially useful model for olfactory processing has been proposed by Granger, Lynch, and Ambros-Ingerson [44-48] which we believe provides some preliminary answers to questions of this kind. This model deals with the interacting structures of the olfactory bulb (which receives input from the olfactory receptors via the olfactory nerve) and the piriform cortex, as they appear in olfactory mammals such as the rodents and lagomorphs. It was developed to study the function of these structures based on their known anatomy and physiology, and its emergent computational properties, rather than appearing by design, were discovered upon analysis of simulation results. Function is acquired by an unsupervised learning rule, effectively based on coactivity, which models long-term potentiation. Operation is dependent upon the statistical properties of large assemblages of neurons with sparse, combinatorial interconnections and coarse-valued weights.

In this paper, we discuss this model and the features which make it amenable to implementation, and we describe ongoing efforts toward such an implementation in analog CMOS integrated circuitry. The low-resolution weights and coarse, unidirectional weight changes allow a parallel implementation of the learning rule, using floating gates for nonvolatile analog weight storage. Designs of test circuits for macrocells which implement the required functions are presented, and the integration of these macrocells into a complete network is discussed.

2. The Model

The interested reader is referred to the work of Granger et al. for details of the olfactory model [44-48]. The essential features of the model which are relevant to the proposed implementation are summarized as follows. The olfactory bulb receives input from the olfactory receptor neurons in a somewhat topographic fashion: a particular type of receptor cell (i.e., a receptor which responds to particular chemical stimuli) projects its axons along with those of similar cells to a delimited area of the olfactory bulb which is denoted a glomerulus. The aggregate firing rate of these input cells is regarded as the input to the corresponding glomerulus. There are many glomeruli in the olfactory bulb, each associated with a different type of receptor cell, and thus the system input collectively may be regarded as a vector. The input components, which are