

# Neural Development on the Ubichip by Means of Dynamic Routing Mechanisms

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**Abstract.** The ubichip is a bio-inspired reconfigurable circuit developed in the framework of the european project Perplexus. The ubichip offers special reconfigurability capabilities as self-replication and dynamic routing. This paper describes how to exploit the dynamic routing capabilities of the ubichip in order to implement plastic neural networks. We present an approach for dynamically generating a network topology, where synapses among neurons can be created or destroyed depending on the input stimuli. We describe their implementation in the ubichip, and we analyse the resulting network topology and the network development. This work constitutes a first step toward plastic neural circuits exhibiting more realistic biological features.

**Keywords:** ontogenetic circuits, synaptogenetic circuits, dynamic topology, neural plasticity, reconfigurable circuit, dynamic routing.

## 1 Introduction

The ubichip [1] is a custom reconfigurable electronic device developed in the framework of the Perplexus project [2]. The ubichip is capable of implementing bio-inspired mechanisms such as growth, learning, and evolution. These bio-inspired mechanisms are possible thanks to reconfigurability mechanisms like dynamic routing, distributed self-reconfiguration, and a simplified connectivity. The ubichip offers an interesting set of reconfigurability mechanisms for supporting networks featuring different types of neural plasticity.

Different approaches have been proposed for automatically generating neural networks' topologies. Evolutionary artificial networks [3], for instance, generate a network from a description contained in a genome. Each link of the network is somehow coded in the genome. Other common approaches include growing and pruning algorithms [4]. Such algorithms add or remove neurons to or from a network, according to its computing or generalization capabilities. These approaches are useful for computing purposes but biologically unplausible given the topological dependency on a specific task performance. Moreover, it has been shown that network's topology plays a fundamental role in brain processes like learning and consciousness [5], making brain's topology and plasticity one of

the key phenomena to draw inspiration from in order to model and understand such type of systems.

Ontogenetic (or developmental) neural models arise as an alternative approach for building neural networks. From a set of initial construction rules and conditions, the network is built under a constant interaction with the environment. In [6], Cangelosi uses a genotype for encoding the construction rules of a neural network. This approach is more biologically plausible given the undirect coding (genotype) of the resulting network (phenotype). In real life, an individual's phenotype is not directly derived from its genotype, but it is highly influenced by environmental stimuli during life-time. This phenotypic development is also driven by physical constraints that allow to bound the brain's size, the number of dendrites per neuron, an axon's length, and the resulting neural structure. Physical constraints are very rarely taken into account by incremental network building models.

This paper presents an approach for exploiting the ubichip's reconfigurable capabilities, more specifically the dynamic routing, in order to implement plastic artificial neural circuits. The plastic neural model presented in this paper allows a network to be developed in function of the interaction with the environment, more precisely, in function of the input stimuli. It permits to implement synaptic plasticity through the dynamic creation of network connections –synaptogenesis– and the dynamic destruction of unused connections –synaptic elimination–. It must be noted that this paper focuses on the network topology generation and not on its ability to solve a task. Related work is reported in [7], where the ubichip has been used for implementing synaptogenetic networks. The work presented in this paper extends the results presented in this previous work by enhancing the neural model and analysing the network development.

This paper is structured as follows: In section 2 we introduce the ubichip. Section 3 gives a short introduction to neural circuits. Then, section 4 describes our model for generating neural topologies. Section 5 describes the implemented networks and the results obtained from them. Finally, section 6 concludes.

## 2 Ubichip

The ubichip is mainly composed of three reconfigurable layers interconnected among them. Units from each of the three different layers are grouped for forming a macrocell. A macrocell contains thus four *ubicells* connected to a *routing unit* and a *self-reconfiguration unit* as described in [1].

The first layer is an array of *ubicells*, the reconfigurable logic elements used for computation purposes. A *ubicell* is composed of four 4-input look-up tables (LUT) and four flip-flops (DFFs). These *ubicells* can be configured in different modes like counter, FSM, shift-register, 64-bit LFSR, adder, subtracter, etc. An *ubicell* can also implement a simple 4-bit processing element being part of a SIMD multiprocessing platform, and  $n$  *ubicells* can be merged to create a  $4n$ -bit processor.

The second layer is made of *self-reconfiguration units* that allow part of the circuit to self-replicate somewhere else on the chip, without any external

intervention. This mechanism is not exploited by the work presented in this paper, but more details about it can be found in [8].

Finally, the third layer contains *dynamic routing units* connected to their eight neighbors that permit the ubicells to dynamically connect to any part of the circuit. Therefore, growing and developing cellular systems requiring the ability of creating and destroying paths at runtime, in order to connect newly created cells, can take advantage of this new feature. Based on identifiers and a concept of sources and targets trying to reach a correspondent with the same ID, this mechanism looks quite similar to the system described in [9], while having enhancements on different aspects. The ID, being stored in a routing unit, can be dynamically modified by an ubicell connected to it, a feature fully exploited by the experiment described in section 4. The basic idea of the routing algorithm is to construct paths between sources and targets by dynamically configuring multiplexers, and by letting the data follow the same path for each pair of source and target. Sources and targets can decide to connect to their corresponding unit at any time by launching a routing process. These routing processes are launched by the ubicells, and so a neuron, for instance, can decide, depending on its activity, to create a new connection to another neuron. During a routing process, after the identification of the sources and targets based on their IDs, a phase of path creation executes a breadth-first search distributed algorithm, looking for the shortest path. If such a path exists, then the multiplexers are configured accordingly, while if not, the ubicell is notified about the failure of the routing process. When a source and a target have been connected, then the path is fixed and data can be directly sent at any time, until the path is destroyed.

These dynamic routing mechanisms, along with the computational capabilities offered by the ubicells, will allow us to tackle the modeling of neural circuits exhibiting intricate and dynamic topologies.

### 3 Neural Circuits

Mammals' brain is a complex system composed of millions of neurons interconnected by an intricate network. The topology of such network, and the developing mechanisms that allow to form it, remain a challenging study field for neuroscientists. Several studies have attempted to find characteristic patterns in such connectivity in order to model these neural circuits. These studies have found that neural interconnectivity is neither completely regular nor fully random, but it exhibits an intricate organization [10].

A key aspect on complex systems is their topology. Possible topologies range from regular arrays, where each node is strictly connected to neighbor nodes forming a regular grid, to random network structures, where nodes are randomly linked independently of their positions or their previous connections. Somewhere between these regular and random networks, we find the so-called small-world networks [11]. A small-world topology is characterized by connections with neighbor nodes mixed with some degree of randomness, exhibiting a high degree of local clusterization. Small world networks are mainly characterized by the short

path length that connects every two nodes, and have been shown to be very robust when erasing nodes. In small-world networks we can observe two key aspects: a particular degree distribution (the distribution of the number of connections per node) and a low mean shortest path. Unlike regular or scale-free networks [11], small-world and random networks exhibit a Poisson degree distribution. This means that most of the nodes are moderately connected, and some few are highly and lowly connected.

Recent studies have concluded that neural circuits exhibit small-world connectionism [10]. In part, this explains the brain robustness in presence of neural death. Additionally, the brain structure exhibits a constant plasticity, that implies that brain's topology is not static, but dynamic. Neurons and synapses are constantly being created and destroyed at time scales of minutes or hours. During early mammalian development this plasticity is very high, for achieving a certain stability in the adult stages. However, neural and synaptic birth and death remain active during the whole individual's life-time.

## 4 Neural Plasticity on the Ubichip

Given the dynamic routing mechanisms of the ubichip, it results an interesting digital hardware platform for implementing connective systems with dynamic topologies, more precisely in our case, developing artificial neural networks. The current implementation of the model considers the initial existence of a set of unconnected 4-input neurons, where dendrites (inputs) and axons (outputs) are connected to dynamic routing units which are previously configured to act as targets and sources respectively. The connectivity pattern will be further generated during the neural network life-time.

We use a simplified neuron model whose implementation on the ubichip requires only six macrocells. Each dendrite, including the required logic for creating and destroying a synapse in a probabilistic way, is implemented in a single macrocell. Two more macrocells are used for implementing the soma (cell body of a neuron) and the axon: the computation of the activation function, the neuron output, and the management of the dynamic routing ID modification.

The neuron model is defined by a stochastic activation function  $y = f(\sum i)$  where,  $i$  is the activity at the inputs of the neuron, and  $f()$  is an activation function given by a probability  $P$  of firing that is  $P = 0.25 * \sum i$ . In other words, if the four inputs are active the neuron fires, if no input is active the neuron does not fire, if a single input is active the neuron has a probability of 25% of firing, 50% for two active inputs and 75% for 3 active inputs.

An important aspect to consider in the network generation model, is the eventual impossibility of creating a connection between two existing nodes because of routing congestion. More than a limitation of the implemented model, it constitutes an interesting feature. Physical routing constraints are present in biological and our artificial network, and this similarity will certainly make, in both cases, more likely to create connections between close neurons than between remote

neurons, generating specific clustering patterns. However, the size of the models presented in this paper are not still large enough for exhibiting such clustering.

The work presented in this paper uses the same activity-driven synaptogenetic approach for generating the network's topology that was presented in [7]: more active neurons have a higher probability of getting connected than less active neurons. Additionally, the model presented in this paper also allows to eliminate unused synapses: a dendrite connection is destroyed after a certain time of inactivation.

The activity-driven synaptogenesis approach [7] is based on the principle that more active neurons are more likely to get connected than less active neurons. This principle is inspired by a phenomenon called ocular dominance plasticity [12] that has been observed in an experiment called monocular deprivation, where a kitten's eye is occluded during early life. In this experiment, it has been observed that synaptic connections on the visual cortex are more strongly connected to the more stimulated eye.

The activity-driven synaptogenesis draws inspiration from this principle for building the neural network topology. The complete network is composed of two inputs which are stimulated with different firing rates. The most excited neurons may have more chances to get connected than the less excited ones. On the same way, the neurons that get connected to the input neurons will be activated by them and may also increase their possibility of getting connected. We also consider the case where an existing connection is not excited any more (or poorly excited). In this case we introduce to the model the concept of *activity-driven synaptic elimination*: use it or loose it!

In this paper we present a complete implementation of both mechanisms, we excite both inputs at different firing rates, we analyse the network topology generated from it, and we analyse the synaptogenesis evolution during time.

## 5 Experimental Setup and Results

The implementation on the *ubichip* uses the neuron model described before, including the synaptogenetic process. The synaptogenetic process is implemented in a distributed way, separating some actions to be carried out in the dendrites and some others to be carried out in the axon. Initially, a set of unconnected neurons is configured in the *ubichip*. Each dendrite has a unique ID, and they are constantly attempting to get connected to an axon with the same ID. If the dendrite is successfully connected, the connection remains and the dendrite does not attempt connections anymore.

From the axon's side, IDs are initialized to a value of 0, preventing it to getting connected since there are no dendrites with such ID. Axon's IDs can be randomly modified, with a certain probability, at each firing of its respective neuron. The more a neuron fires, the higher will be the probability of modifying its ID. Consequently, the more an axon changes its ID, the more probabilities it will have to get connected to different dendrites.

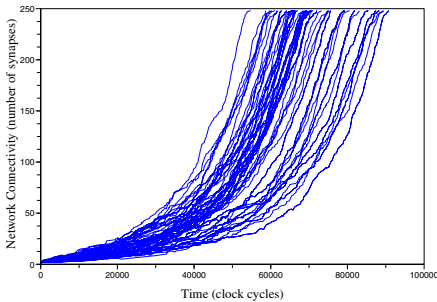
We implemented a network composed of 2 inputs firing at different activation rates, and 62 4-input neurons disposed in an array of  $8 \times 8$ , leaving place for the circuitry that generates the input stimuli. Each of the two inputs is connected to a dendrite of a neuron and the remaining 3 dendrites of the input neurons can be further connected to any other neuron on the network. We measured the synaptogenesis rate over time and we analysed the resulting network.

### 5.1 Synaptogenesis Rate

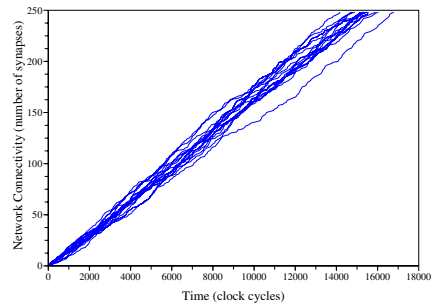
We ran 50 experiments with both inputs firing at regular firing rates. Each of the two inputs has a probability of 50% and 25% of generating an impulse at each clock cycle. Figure 1 shows the evolution of the synaptic formation curves for the 50 runs. At the beginning, the network is unconnected and connections are initially created at a very low rate: during the first 20000 clock cycles, up to 20 synapses are created. At the end of the network development process the synaptogenesis rate is considerably increased: during the last 20000 clock cycles, up to 200 synapses can be created.

For the sake of comparison we performed the same experiment with a random synaptogenetic network. Unlike the activity-driven approach, such type of network allows the modification of the axon's ID independently of the activation of the neuron. Figure 2 shows the resulting synaptic formation curves of the random approach on 15 experiments. From this figure, we can observe that the random synaptogenesis growing rate approaches a linear function. Since any axon can get connected to any dendrite at any time, the probability of creating a synapse remains almost constant during the network construction.

The activity-driven approach provides a more biologically plausible synaptogenesis growth. At the beginning, synapses are less likely to be created than at later stages of the network's development. From the figure 1, it can be observed that the probability for a synapse of being created increases over time. This relation can be explained by the initial inaccessibility of non-stimulated axons, and by the fact that only stimulated neurons can assign valid IDs to their respective



**Fig. 1.** Activity-driven synaptogenesis development rate



**Fig. 2.** Random synaptogenesis development rate

axons. This differential connection creation probability also explains the higher amount of time required for the activity-driven network for being fully created. The network construction can be seen as a growing network, where nodes and links are added in function of the existing nodes activity.

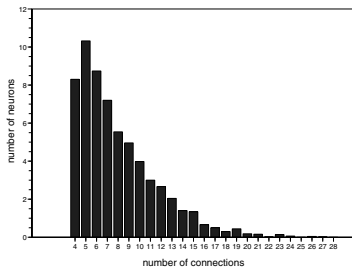
From figure 1, it can also be observed that the synaptic elimination mechanism is effectively having an effect on the created network. It is in fact destroying some synapses from time to time (observed as slight decreases in the synaptogenetic curve). However, it does not seem to have a significative impact on the overall growing curve since synaptic destructions are rapidly compensated by new synaptic creations. The real impact of such pruning processes is mostly observed in the resulting network structure, because it will prevent the existence of neurons with high number of intermediate steps to input neurons.

## 5.2 Resulting Network Structure

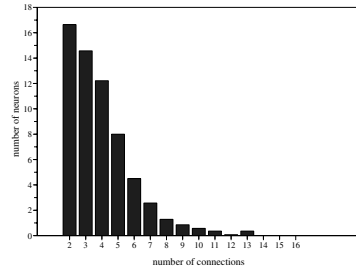
In [7], we presented some preliminary results about the network structure that can be obtained with the activity-driven approach. However, the model considered in this previous work considers the usage of a 2-inputs neuron. In this previous work we concluded that the degree distribution of the network approached a power law distribution, which is the characteristic distribution of scale-free networks. However, in this paper we found a different degree distribution. The fact of increasing the number of inputs of a neuron from 2 to 4 increases also the total number of links in the whole network and reduces thus the probability of an axon to remain unconnected.

Figure 3 shows the mean degree distribution, over 50 experiments, of the network of 4-input neurons obtained by the activity-driven synaptogenesis. For the sake of comparison we show also, in figure 4, the degree distribution obtained in [7] for a network of 2-input neurons.

The degree distribution of figure 3 shows that, in average, there are 8 neurons with only 4 connections (the 4 inputs and no output), around 10 with a single connection to the axon, and some few with a lot of connections (up to 23



**Fig. 3.** Degree distribution of a 4-inputs neuron network obtained by activity-driven synaptogenesis



**Fig. 4.** Degree distribution of a 2-inputs neuron network obtained by activity-driven synaptogenesis. From [7].

connections). The distribution of the figure suggests a rough approach to a Poisson distribution, which is the characteristic distribution of small-world networks.

On the other hand, the degree distribution of figure 4 suggests more a Power law than a Poisson distribution. In this network there are much more unconnected axons than in the 4-input neuron network. This can be explained by the reduced number of existing connections in the 2-input neuron case. From these two figures one can conclude that both distributions can be seen as a Poisson distribution displaced to the left. More connections per node there are in the network, more the distribution will displace to the right, since the probability of leaving an unconnected axon will be lower, and thus the degree distribution will fit more clearly a Poisson distribution.

### 5.3 Ocular Dominance

Concerning the ocular dominance aspect, we measured the resulting connectedness of both inputs to the network. We considered two different networks excited at different firing rates: 1) The first network is the same as described in subsection 5.1, the first input of the network is excited at 50% and the second at 25%, and we ran 50 experiments for obtaining the average connectivity of both inputs. 2) The second network is excited at 50% in the first input and the second at 6.25%, and we ran 20 experiments.

Figure 5 illustrates the average number of neurons connected to both input neurons in both networks. From here, white columns refer to the least active input neuron and black columns refer to the most active one. The figure represents the number of attainable neurons in a certain number of steps represented by the horizontal axis. In our case, we use the term step for indicating the degree of separation between two nodes in a graph, or between a node and a link.

Figures 6 illustrates the number of attainable synapses in a certain number of steps. It shows the average number of synapses connected to each input neuron in both networks. This figure provides a different information than the previous one because two neurons can be directly connected through several synapses, and they

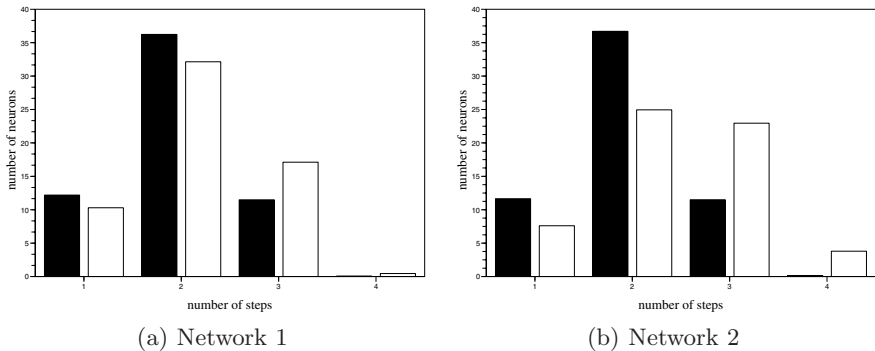
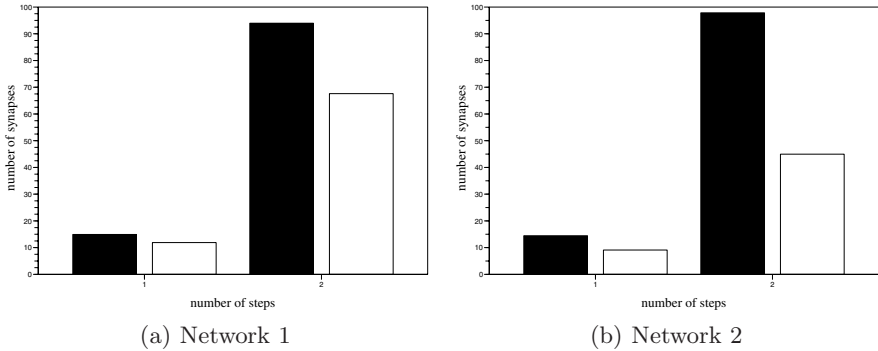


Fig. 5. Neural connectivity of input neurons





**Fig. 6.** Synaptic connectivity of input neurons

will be more strongly connected than two neurons connected with a single synapse, so the connectivity between them cannot be considered to be equivalent.

From the connectivity distribution in figure 5 it can be observed that, as expected, the most excited input can reach more neurons after one and two steps. However, at a third step there are more attainable neurons for the less excited input neuron. This can be explained because of the saturation of the network, The most active input network can reach almost 90% of the neurons in at most two steps, so the remaining 10% is attainable in 3 steps. By comparing figures 5(a) with 5(b) and 6(a) with 6(b), it can also be clearly verified that when the difference in the excitation of a pair of inputs is increased, the difference in the connectivity of these two inputs is increased as well.

## 6 Conclusions

This paper presented the model and implementation of a neural circuit able to grow by physically creating and destroying synaptic connections depending on neural activity. The described model includes a synaptogenetic mechanism that allows to create connections, and a synaptic elimination mechanism that allows to prune the network. Both, synaptic creation and elimination are performed following an activity-driven approach: most active neurons have a higher probability of being highly connected, and least active synapses may be destroyed.

Even if the presented growing network does not focus on the solution of a task, it can be used in different types of systems. Robotic systems with several sensors can exploit the fact that more active sensors may provide more information for solving the task at hand and could be thus more connected to the neural network. Attention visual systems may exploit the growing feature of this network considering that more active vision fields may provide more relevant information. In general, our approach can be applied to problems where our growing neural system interacts with the environment through sensing interfaces, in order to bias the network formation toward the most relevant inputs.

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