Reducing the Active Paths Interference in the Chialvo-Bak "Minibrain" Model

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***Abstract*—We examine a simple biologically-motivated neural network, the version of the Chialvo-Bak "minibrain", and propose an approach to decrease the negative effect of the active paths interferences in a process of learning new data. For this purpose we use randomly ordered neural network structure with recurrent signal propagation mode. We investigated the network's performance and learning capacity dependence on its nodes' interconnection level. Our simulation study shows that the proposed approach needs on average 40% less number of learning steps for learning the same set of patterns and has higher learning capacity compared to the existing method.**

***Index Terms*—Hebbian learning, neural network, pattern recognition, reinforcement learning.**

I. Introduction

In this paper we propose an approach to improve the performance of the "minibrain" model suggested by Chialvo and Bak [1] by decreasing the negative effect of the active paths interferences in a process of learning new data, at the same time resembling the changes to the biological learning processes of the animal's brain.

First of all, we do not use the fixed layered structure of the network, but an initially unstructured set of neurons with randomly chosen weights. Also we use diluted connectivity instead of fully interconnecting every neuron in the attempt to avoid the negative effect of path interference. For the same purpose we adapt the algorithm to the recurrent signal propagation mode in place of the feedforward one.

Formulated as early as 1949, Hebbian rule [2] has been an important milestone for both neurophysiology and computer science. It was the first and the only plausible learning rule for artificial neuron networks. The rule was successfully used in various applications, including the model of bee's foraging in an uncertain environment [3] and human decision making [4].

However upon a closer view we notice a few drawbacks while applying the method in its present form. Firstly, it is a self-destruction of a pre-learned information in an attempt to adjust the weights for storing new information. In the canonical example of [5], Edelman compares a mouse's behaviour with behaviour of a robot, controlled by a neural network in a certain environment. The result shows that after the environment changes, the robot seldom retrieves pre-learned knowledge, unlike the mouse. The reason is that the field of coefficients of neural network is destroyed by the newly learned information. This example presents the importance of storing a pre-learned data while being able to perceive the new data without any overlap. Our paper presents the approach of creating the network capable of storing new information without loosing the old information.

Another drawback of Hebbian learning is an autocorrelation term of the learning rule. During a correlation of presynaptic and postsynaptic neurons' activity, weight growth causes a higher postsynaptic potential and therefore even more weight growth. It causes the exponential weight growth and leads to destabilisation of the network [6]. Although in an earlier paper [7] Hebb had introduced the mechanism of decreasing the synaptic weight under certain conditions, he has excluded it in its final version [2]. Consequently, it is unlikely that applying only the pure Hebbian rule will result in an entirely adaptive system capable of task-oriented learning.

To solve the described constraints without loosing the biological plausibility, i.e. keeping it consistent with learning processes of the animal's brain, Bosman et al. suggested a model of neural network in which both Hebbian and reinforcement learning occur [8]. According to the contemporary biological studies, reinforcement mechanism was observed in biological learning processes and was successfully used to interpret the activity of dopamine neurons to mediate reward-processing and reward-dependent learning in non-human primates [9], and modulate cortico-striatal synaptic efficacy in humans [10], also solving problems, including robot control, elevator scheduling, telecommunications and chess [11].

In the "minibrain" model of Bosman et al. [8] the extremal ("winner-takes-all") dynamics is used, inspired both by earlier SOC models [12] and the SOM [13], which considerably improves learning performance and provides a fast and highly adaptive learning system. However the network's learning capacity remains the crucial issue due to the active paths interference that destroys the formed weight matrix in an attempt to adapt itself for the new patterns. In this paper we thoroughly investigate this phenomenon and suggest the way to reduce the negative effect of the active paths interference.

II. Proposed Approach

The common problem of storing the large amount of input patterns into the network is the interference of new learned data with previously learned data. When several input patterns are applied to the neural network to be learned, the negative effect of the paths interference arises. The active

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paths overlap when the strongest connection from the different input patterns point to the same intermediary neurons. As result, the learning of something new causes forgetting of an old data.

There may be several reasons, which give rise to such a situation. First of all, from the active input neuron the path of activity runs along the strongest synaptic connections to the corresponding output neurons. In certain situations an established path can be completely “wiped out” by an attempt to learn new data, so that connection of the previously learned pattern is no longer the strongest. Also the competition between the activity path, formed in previous steps, and newly forming active path can happen. Such a competition often erases or partially destroys the old path and correspondingly leads to forgetting of old data by the network.

Secondly, according to the “minibrain” algorithm, in the case of the incorrect output pattern, the mechanism of decreasing the strength of recently formed synaptic connections is applied. This almost certainly removes the previously formed synaptic connection from the active level of synapses and forms another one, which produces a different output pattern. Correspondingly, the large amount of the incorrect output patterns causes a large change in the geometry of the active level and, hence, in the weight matrix of the network connections. This causes a so-called “avalanche” in the network landscape [1].

Solving the problem of path interference we introduced several improvements to the algorithm. Firstly, we keep the overall network activity at low level. In this way the formation of the new network activity patterns has less influence to the already existing paths, allowing to coexist the both [14]. The activity of the network over a certain period of time can be calculated as a fraction of active neurons to the total number of all neurons.

Secondly, more than one neuron is needed to excite a postsynaptic neuron. Although this point is mentioned in the Hebbian postulate [2], often it is violated. This restriction limits the probability of any neuron to influence several activity paths and thus reduce the chance of their overlapping.

Thirdly, we exploit the diluted network which means that rather than connecting every neuron to all others we interconnect them based on a certain probability. This diminishes the chance of involving the same neurons forming the activity paths for different input patterns. However, the level of activity depends strongly on the level of dilution and our investigation show that the most optimal level of dilution would be the 80 % of the full network interconnection (see Fig. 4).

Fourthly, we deliberately avoid the direct connections between the neurons' set dedicated for the input with the neurons responsible for the output. Otherwise, the direct connections extend the learning period or corrupt the final result. This happens because these connections cannot fit all set of learning patterns and if they do not fit the current learning pattern, it takes long time to reduce such connections' weight to zero; besides according to the learning mechanism, all other weights are affected by the changes.

Finally, we do not use a structured network but employ the randomly interconnected set of neurons with dedicated array for providing an input and another array employed to receive an output. The mode of signal propagation is recurrent and the output is taken only when the network's state is settled. The network determines whether it has reached a fixed point by recording each state of the network and comparing it with the subsequent state.

III. Simulation Results and Discussions

Our experiment proves that the proposed network architecture with recurrent signal propagation have higher performance comparing to the original method [8]. According to the proposed approach we created the neural network of 200 neurons and studied it under various conditions. We dedicated 10 neurons for input and another 10 neurons for output and taught the network to 20 different input patterns, associating them with certain non-repeating output patterns chosen by the network. Every experiment was repeated 20 times to calculate the mean value of the learning efficiency.

To measure the efficiency of the learning process we selected two parameters: number of learning steps and learning performance. The latter can be calculated as the ratio of the average *a priori* number of performed learning steps to the actual number of steps, which were needed to learn the set of applied input patterns and to associate them with the output patterns.

Fig. 1 presents the result of the experiment and shows the comparison of the feedforward and the recurrent propagation signal modes in the neural network as a function of the input pattern number. The difference in the performance increases with the higher number of applied patterns. If for one or two input patterns the learning performance is similar with the difference around 0.05, the difference grows up to 0.3 for 10 input patterns.

The similar behaviour is observed counting the number of learning steps. Fig. 2 shows the comparison of the average number of learning steps performed by the neural networks with the feedforward and the recurrent signal propagation modes as a function of the input patterns number. While using the recurrent network, it is necessary to perform much less learning steps to adapt the weight matrix to the larger number of learning patterns. For example, we need only 1230 learning steps to learn 6 input patterns, whereas the existing approach needs 2120 learning steps.

Another important observation is that the network's capacity is lower while learning with the feedforward signal propagation mode because in our experiment the network could not learn more than 10 input patterns, whereas it took around 5000 learning cycles for recurrent network to adapt its weight matrix for 12 learning patterns, as can be seen in Fig. 2.

We took a closer look at the dynamic of the synaptic weight changes of the network. The rate of weight change of two randomly taken connections is shown in Fig. 3. It presents how different neurons participate in various activity paths formation. While the connection of the feedforward network finds its equilibrium quite fast and from 5800th learning step remains unchanged, the weight in the recurrent network keeps adjusting its value during the whole process of the experiment.

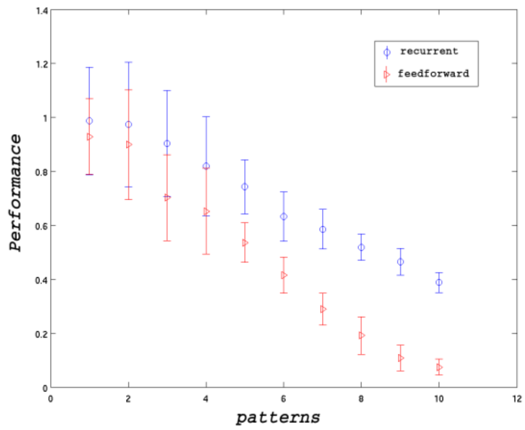

Fig. 1. Comparison of feedforward and recurrent signal propagation modes in the neural network as a function of the input patterns number.

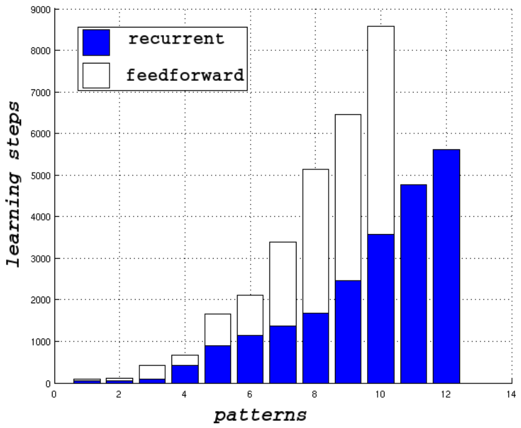

Fig. 2. Comparison of the average number of learning steps performed by the neural networks with feedforward and recurrent signal propagation modes as a function of the input patterns number.

The fluctuations shown in Fig. 3 are caused by path interferences and are also decreasing as the network redistributes the weights and forms the alternative paths to associate the input patterns with the most optimal output patterns.

The phenomenon can be explained by taking into consideration the way the neural network stores the learned information. Intuitively we could presume that the learning efficiency of the network grows with the number of neurons. However, this is only valid to a certain extent. The applied input pattern activates the corresponding neurons and causes them to fire further to the post-synaptic neurons. Those neurons, however, activate only if their input weights are strong enough to cause the accumulated signal that exceeds the firing threshold.

Due to these aforementioned activation constraints, the activity paths are formed in the network. Corresponding to each input, the most probable signal propagation will follow the associated pattern. However, when the number of input patterns or the inter-connectivity level increases, the activity paths overlap, and thereby destructing each other and corrupting the output result. Fig. 4 shows, that the performance degrades beyond the 80 % of the full network interconnection.

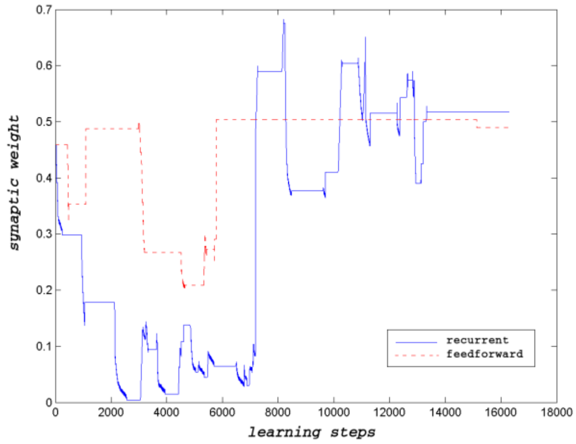

Fig. 3. The rate of synaptic weight change in the neural networks of feedforward and recurrent signal propagation modes.

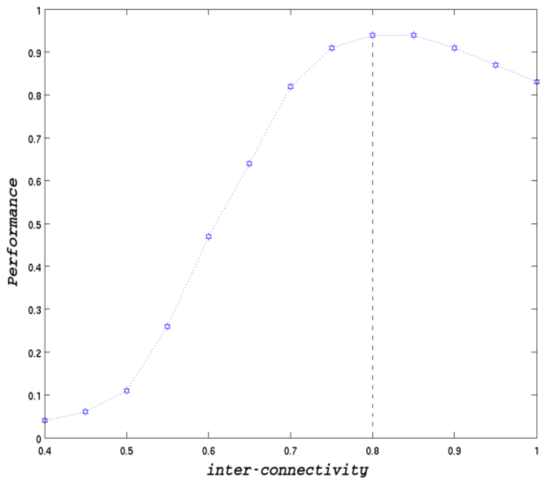

Fig. 4. Performance of the recurrent network as a function of the connection probability (dilution).

Although the low interconnection level leads to longer adaptation time, the trade-off must be find because the slow-down in the learning rate starts to predominate when the quantity of neurons exceeds the optimal number or the network is fully interconnected.

IV. Conclusions and Future Work

This paper investigates the self-learning neural network and the ways to decrease the negative effect of the active paths interferences in a process of learning new data without losing the previously learned one. Although a complete analytical understanding of this phenomenon is still to be developed, the underlying mechanism behind this behaviour is identified and several improvements have been suggested.

The results can be improved by changing the set of input patterns to ones with fewer similarities among each other. This makes the input patterns more distinctive for a neural network as a higher number of different input neurons will be activated. This diversifies the activity paths and reduces the corruption of output which would be caused by overlapping of new learned data with pre-learned ones.

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